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Optimisation of Support Parameters in Mining Terrain using Artificial Intelligent Techniques

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Sudhir Kumar Kashyap

Optimisation of Support Parameters in Mining Terrain using Artificial Intelligent Techniques

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by

Sudhir Kumar Kashyap

Under the guidance of

Prof. Dayal R. Parhi **Amalendu Sinha**

(Supervisor) **(Co-supervisor)**

Department of Mechanical Engineering
National Institute of Technology Rourkela
Orissa (India)-769008

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Declaration

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgement has been made in the text.

(Sudhir Kumar Kashyap)

Date:

Department of Mechanical Engineering

NATIONAL INSTITUTE OF TECHNOLOGY

Rourkela, Odisha, INDIA- 769008

CERTIFICATE

This is to certify that the thesis entitled ***"Optimisation of Support Parameters in Mining Terrain Using Artificial Intelligent Techniques"*** being submitted by **Mr. Sudhir Kumar Kashyap**, Roll No. **50703006**, to the Department of Mechanical Engineering, National Institute of Technology, Rourkela for the partial fulfillment of the award of the degree of **Doctor of Philosophy** is a record of bona fide research work carried out by him under our supervision and guidance.

In our opinion the thesis is of the standard required for the award of Doctor of Philosophy in accordance with the prescribed requirement of the institute. To the best of our knowledge the thesis which is based on candidate's own work has not been submitted elsewhere for the award of any degree or diploma.

(Prof. D.R.Parhi)	(Dr. A. Sinha)
(Supervisor)	(Co-Supervisor)
Department Mechanical Engineering	Director
National Institute of Technology	Central Institute of Mining and Fuel Research
Rourkela-769008,Odisha,INDIA	Barwa Road,Dhanbad-826015,Jharkhand,INDIA

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Synopsis

This dissertation describes work in the area of Artificial Intelligence technique in underground mine support system. India has a large reserve of coal as compared to other fuel energy sources. Exploitation of coal with full safety has been a challenging job since years. Ground control operation in underground mine is an imprecise work as we are dealing with a material produced by nature. Behaviour of soil and rock in mine during excavation can hardly be predicted with the existing knowledge. Due to this reason roof falls continue to remain the single largest killer. As many as 61% of the incidences, which is 28.5% of total fatalities are due to roof fall. Roof fall, coal bumps and massive pillar failure in coal mines represent serious ground control problem resulting reduction in coal mine safety. Mine supporting system has greater role to play in preventing roof fall accidents. Whenever falls have taken place either no support was provided or the supports were inadequate in capacity and improperly set. During extraction of pillar in galleries roof are supported with roof bolts as well as standing support like prop, cog, chock etc. depending upon their inbuilt load. Under this condition, till date we have been using empirical approaches to mine support design. Consequently, expert knowledge can have a greater role to play in avoidance of accident using accurate measurement optimization of various support parameters and analysis of data a prediction based on previous results using Artificial Intelligence techniques.

In the current research mainly three techniques i.e. Artificial Neural Network, Fuzzy Logic and rule based technique and their hybridization have been used for finding the parametric values required during the prop installation in underground mines.

ANN is a computational intelligence model that consists of nodes that are connected by links. Each node performs a simple operation to compute its output from its input, which is transmitted through links connected to other links. This relatively simple computational model because on the structure is analogous to that of neural system in human brain-nodes corresponding neurons and links corresponding to synapses that transmit signals between neurons. Human brain is modeled as a continuous-time nonlinear dynamic system in connectionist architectures that are expected to mimic brain mechanism to simulate intelligent behavior. Such connectionism replaces symbolically structured representations with distributed representations in the form of weights between a massive set of interconnected neurons. In this current research work input parameters taken are Rock Mass Rating (RMR), distances of props from the face , rock density, working height, seam thickness, width of gallery and charge per hole where as target output is setting load to be given to the props.

Backpropagation Neural Network (BPNN) has been used to train the network for optimizing the mine support parameters i.e. setting load given to the props erected for the purpose of supporting freshly exposed roof during underground mining excavation in Bord and Pillar minng. Backpropagation algorithm is one of the robust techniques as it provides the most efficient learning procedure for multilayer neural network. By simulation the result was validated with the target output until the network error has converged to threshold minimum.

Uncertain and unpredictable activities which often happen in mining could also be handled by the Fuzzy Logic theory. The fuzzy sets may be taken as an important tool for the modeling of human reasoning to minimise uncertainty. It provides a systematic calculus to deal with imprecise and incomplete sensory information linguistically, and it performs numerical computation by using linguistic labels stipulated by membership function. Moreover , a selection of fuzzy if-then rules forms the key component of a Fuzzy Inference System that can effectively model human expertise in a specific application.

In a rule based system , the knowledge of the environment is stated in the form of rules. These are the major types of knowledge representation formalities used in expert systems. There are three main components of typical rule based system i.e. the working memory, the rule base and the inference engine. The working memory contains information about the particular instant of the problem being solved. The rule base is a set of rules, which represent the problem solving knowledge about the domain . A rule contains a set of conditions (antecedents) and a set of conclusions (consequents). The inference uses the rule base and the working memory to derive new information. The rule base controller is basically a look table technique for representing complex non-linear system.

Hybridization of the above mentioned techniques were also used for optimization such as ANN, Fuzzy, ANN-Fuzzy, Fuzzy-ANN, Rule Based technique, Rule Based Fuzzy, Rule Based Neural, Rule Based Neuro-Fuzzy (RBNF) and Rule Based Fuzzy- Neuro (RBFN) techniques and targeted output were validated with the actual data. RBFN and RBNF were found to be most suitable and appropriate techniques for obtaining optimum parametric solutions for prop installation in underground mines.

Table of Contents

List of Tables

List of Figures

List of Symbols

$\varphi(.)$	=	Activation function
D	=	Average rock density
Gbell	=	Bell shaped membership function
CHH	=	Charge per hole
DF1	=	Distance of first prop from the face
DF2	=	Distance of second prop from the face
DF3	=	Distance of third prop from the face
DF4	=	Distance of fourth prop from the face
DF5	=	Distance of fifth prop from the face
DF6	=	Distance of sixth prop from the face
A	=	Fuzzy set
Gaussmf	=	Gaussian membership function
HES	=	High setting load on prop
HEC	=	High charge per hole
HIW	=	High width of gallery
HST	=	High seam thickness
HRD	=	High rock density
HIH	=	High height
HID	=	High distance
HIR	=	High RMR
H	=	High
J_v	=	Joint volume
J_n	=	Joint set number
J_r	=	Joint roughness number

J_a	=	Joint alteration number
J_w	=	Joint water reduction factor
LOS	=	Low setting load on prop
LOC	=	Low charge per hole
LOW	=	Low width of gallery
LST	=	Low seam thickness
LRD	=	Low rock density
LOH	=	Low height
LER	=	Less RMR
L	=	Low
MES	=	Medium setting load on prop
MEC	=	Medium charge per hole
MEW	=	Medium width of gallery
MST	=	Medium seam thickness
MRD	=	Medium rock density
MEH	=	Medium height
MED	=	Medium distance
MER	=	Medium RMR
M	=	Medium
$\mu_A(x)$	=	Membership degree of variable x
Neg	=	Negative
p	=	Number of input signal
NB	=	Negative big
NM	=	Negative medium
NED	=	Near distance
U_k	=	Output of network

Y_k	=	Output after activation function (Final output)
Pos	=	Positive
PM	=	Positive medium
PB	=	Positive big
Q	=	Rock mass quality classification
RQD	=	Rock quality designation
RMR	=	Rock mass rating
P	=	Rock load
ROD	=	Rock density
SRF	=	Stress reduction factor
W_{kj}	=	Synaptic weight of neuron
SEM	=	Seam thickness
Trapmf	=	Trapezoidal membership function
Trimf	=	Triangular membership function
U	=	Universe of discourse
x	=	Variable
VL	=	Very low
VH	=	Very High
VLR	=	Very low RMR
VHR	=	Very high RMR
VND	=	Very near distance
VHD	=	Very high distance
VLH	=	Very low height
VHH	=	Very high height
VRD	=	Very low rock density
VHR	=	Very high rock density

VLT	=	Very low seam thickness
VHT	=	Very high seam thickness
VLW	=	Very low width of gallery
VHW	=	Very high width of gallery
VLC	=	Very low charge per hole
VHC	=	Very high charge per hole
VLS	=	Very low setting load on prop
VHS	=	Very high setting load on prop
WHO	=	Working height
WIG	=	Width of gallery
B	=	Width of gallery split

CHAPTER 1

INTRODUCTION

1 Introduction

Underground coal mining is one of the most dangerous phenomena. The roof fall, side fall and failures of structural supports account nearly 65% of total accidents occur in mines. Roof bolting is employed for the weak mine roof after portion of the coal seam removed. In addition to these supports standing prop/support is also installed in conjunction with rock bolting. Ground control operations have been thoroughly researched for the last several decades. Despite these, mine stability problems, such as roof fall, rock bursts, continue to kill or injury people every year. Thus, due to unpredictable behavior of rock masses mining industries rely heavily upon empirical analysis for design and prediction. In such situation expert knowledge in the field of mining may play an important role to solve intricate problems of rock mechanics.

The work described in this thesis is on optimization of support parameters in mining terrain using Artificial Intelligence techniques. Roof Supporting of underground mining has been a challenging job since years. Not much study has been done about the various parameters. In many critical conditions, our fundamental understanding of soil and rock behavior still falls short of being able to predict how the ground will behave. Reason-wise analysis of underground mine accidents reveals that roof falls continue to remain the single largest killer. Controlling ground operation is an 'imprecise' area of engineering due to the fact that we are dealing with a material produced by nature (the ground). Mine Support selection is one important aspect of mine design and planning. Till date, the automation of this task has received little attention. This may be because the concerned knowledge is not yet completely formed, particularly of ground strata rock mechanics. In many cases, rule of thumb and accepted practices are still widely used. Thus subjective judgment is paramount. In order to avoid personal biasness and to make complete use of available human expertise, an expert system would seem to offer a sensible route to computer-aided selection. Empirical approaches to mine design have been widely used since long. Under these circumstances, expert judgments plays a vital role and thus, such accidents can be obviated using the accurate measurement, optimization and analysis of data, a predictions based on previous results using one of the Artificial Intelligence technique i.e. Artificial Neural Networking (ANN). It is a simple and proven computational model, which is analogous to that of neural system in human brain.

In this thesis data were collected for various parameters of mine support from different mines. Initially setting load on prop was estimated taking other parameters like distance of prop from the face, charge per hole, rock density, height of the roof, RMR etc. In simulation data were analysed by different AI techniques e.g. Fuzzy Logic, Artificial Neural Network, Neuro-Fuzzy technique, Fuzzy – Neuro technique and Rule Based Technique and their hybridization. Some of the variable parameters associated with the underground excavation work have been taken as input/output parameter for the network. The technique of simulation of the result has also been presented.

1.1 Background

The present research and development on applications of AI techniques in underground mines or geo-technical engineering have attracted the attention of researchers. Mining is supposed to be one of the oldest professions. Since ancient times woman and man began using stones for their livelihood like food, kill prey for food etc. Due to this, people have been mining rocks and minerals for all kind of their need. Stones were crafted into various weapons and tools until they were discovered that when placed in fire under the right conditions, components of the rock could be extracted to produce metals. This led our ancestors to enter into the Iron age and the Bronze age.

Telerobotics in underground mining is now being applied worldwide. Days are not far-off when our underground mining and surface mining operation would be fully autonomous. In many applications AI techniques are being used to control vehicle operation to interpret obstacle detection data, to conduct path planning and tracking and to optimize bucket loading. In open pit mining operations a system have been developed using AI techniques for automation. Expert systems are being used to select open cast mining equipment and mobile underground mining equipment. AI technique may be used to follow patterns and maintain steady operations. In longwall coal mining, a type of underground mining expert system was created to control the load and speed of a coal shearing machine allowing the operator to operate remotely. AI control mine ventilation system has been studied successfully. Such system can send air where needed and block-off areas not requiring ventilation leading to significant savings and enhanced worker health. In blasting of coal block in mines there has been extensive use of expert knowledge system. Subsidence prediction due to underground excavation is one of the important areas where this technique is used.

Rock mechanics is an important field of today mining in which a mine is monitored for rock failures on a continuous basis with slope design in open pit mining, mine roof support design in underground excavation etc. using empirical methods based on past practices & experiences. It is very well known that rock behavior such as its stability depends upon many factors. For example, bedding plane, faults, joints, insitu-stress field, rock characteristics as well as water can all influence rock behavior. Most of the parameters takes effect simultaneously and have complicated interaction with each other.

Underground mine support equipments like roof bolting, standing support, roof stitching etc. are regularly monitored by different expert techniques. Stress in rock bolts, pull anchorage test load or any other parameters and setting load, pattern of orientation of the props & cogs etc. are measured regularly using data being interpreted with AI techniques.

1.2 Aims and Objectives of this Research

Roof support and side fall control is a fundamental requirement for all underground mining operations. Hard rock mining operations can vary widely depending on the nature of the deposit & geology and thus require varying degrees of ground support to provide a safe working environment as shown in figure 1.1

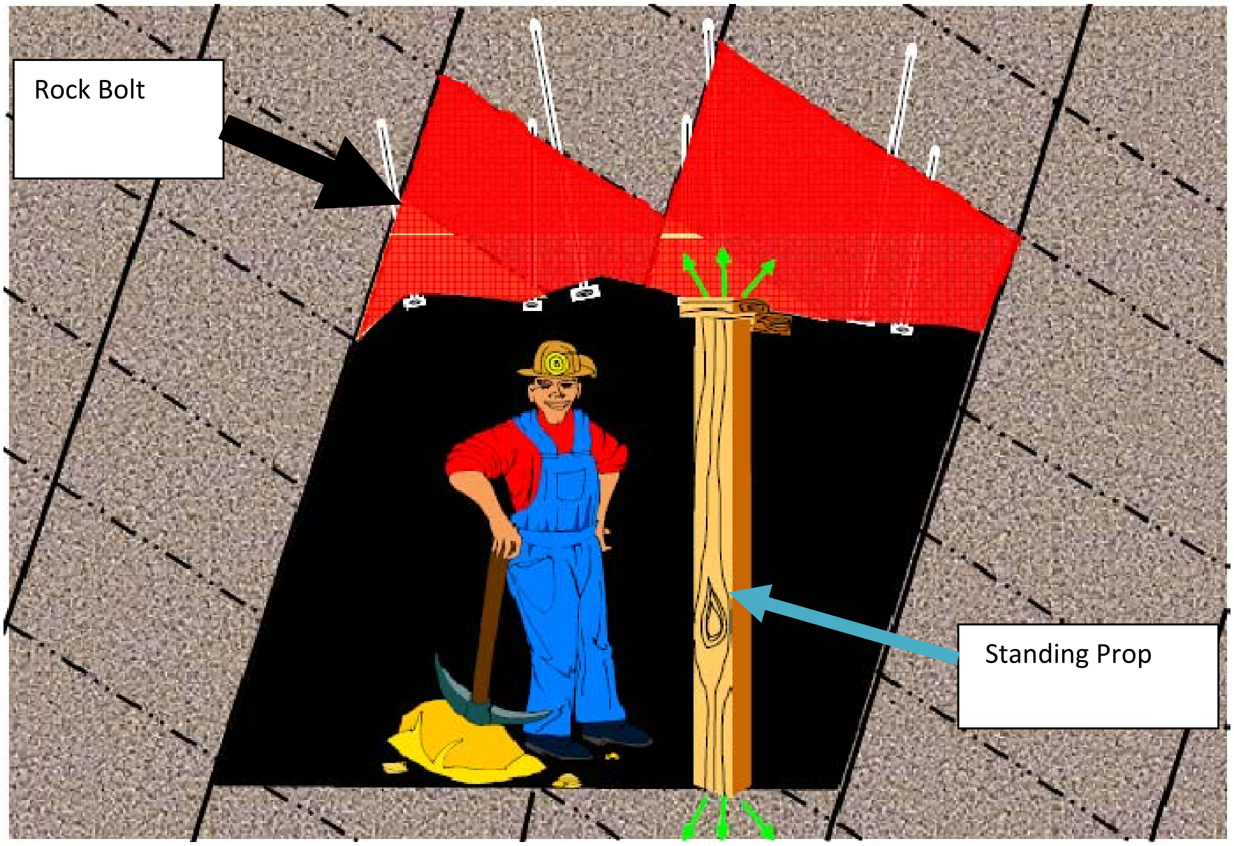


Figure 1.1 Underground mine support showing rock bolt and standing prop (Barczak et al.[1])

Blasting and seismic loading can create additional hazards for the rock strata engineer who must design an effective support system for these critical conditions. Nonetheless, the fundamental aspects of mine roof support remain the same, keep the rock from moving when possible and maintain appropriate & sufficient support as the rock deforms when it is not possible to achieve complete equilibrium. Several developments in roof support technology have been made in the past 20 years, providing a host of new products that improves all three measures of support design; namely strength, stiffness, and stability. Large amount of data and knowledge is available in mining as well as in ground control. However, there are many hindrances associated with the utilization of both data and knowledge. The two main possible difficulties are Model Identification and Knowledge Utilization. In order to cope up with the two difficulties there is requirement to consider the utilization of new and effective computing technologies developed in other fields, especially in Artificial Intelligence. However, there never will be a universal support that will be effective in all conditions. The aim remains to match the support performance characteristics with the ground response - that will always require a site-specific design to achieve support optimization. There are two basic methods of underground coal mining i.e. Bord and pillar mining and longwall mining. The current research finding is concentrated on Bord and pillar mining. About 65% of the accidents occur due to roof and side fall in underground mine. Due to diversified geomechanics of mines various mining parameters are responsible for mine productivity, efficiency and also causing accidents. People have been using empirical relation for analysis of mining parameters on the basis of their working practices, experiences, and knowledge.

The prime objectives of this research recognize the human knowledge and thus optimization in mine support parameters by AI techniques.

1.2.1 Methodologies for Carrying out the Objective of the Research

Various methodologies have been adopted to carry out the objective of the research i.e. optimization of mine support parameters in underground mines. Different researchers have applied different techniques like statistical technique, numerical technique, FEM analysis and also methods of artificial intelligence techniques to get the desired results. In our research different parameters of mine support like standing support, roof bolting have been optimized, analysed and discussed. In optimization the following AI techniques were used to achieve the objective of the research.

1. Artificial Neural Network technique
2. Fuzzy Logic technique
3. Neuro-Fuzzy Hybrid technique
4. Fuzzy-Neuro Hybrid technique
5. Rule Based Technique
6. Rule Based Fuzzy Controller
7. Rule Based Neuro Controller
8. Rule Based Neuro-Fuzzy Controller
9. Rule Based Fuzzy-Neuro Controller.

1.3 Outline of the Research Work

The processes and techniques as outlined in this thesis are broadly divided into ten chapters. Following the introduction and aims & objective in Chapter 1, Chapter 2 presents the literature review of geo-mechanics of mine support system in underground mines, Preloading and its various mechanisms in mine support, mine support parameters, application of neural network technique with backpropagation, fuzzy logic application, neuro – fuzzy & fuzzy – neuro hybrid controller and rule based hybrid controller.

Chapter 3 analyses the different field parameters during excavation.

Chapter 4 describes the optimization of mine support parameters using neural network technique and analysis.

Chapter 5 states the optimization of mine support parameters using fuzzy logic technique and analysis.

Chapter 6 presents the neuro-fuzzy & fuzzy- neuro hybrid controller for optimization of mine support parameters.

Chapter 7 gives the analysis of rule based fuzzy controller, rule based neuro controller, rule based neuro-fuzzy controller, and rule based fuzzy- neuro controller for optimization of mine support parameters in underground mines.

Chapter 8 shows the real data analysis and its comparison with field data.

Chapter 9 explains the overall results and discussion.

Chapter 10 summarizes the conclusions and scope for future work in this field.

CHAPTER 2

LITERATURE REVIEW

2 Literature Review

This chapter presents a literature review of past and recent developments of techniques used for various mining activities related to the current research.

2.1 Introduction

This chapter presents a literature review of past and recent developments in area of optimization of support parameters in mining terrain using artificial intelligence techniques.

A significant amount of research has been completed & published in many aspects related to AI techniques in mining terrain. A reported literature in the area of optimization of support parameters in mining terrain using fuzzy logic, neural network, neuro-fuzzy ,Fuzzy – neuro and rule based techniques are very little. Classification of rock types and design of support structures either upon or inside a rock mass i.e standing prop and/or rock bolts strength and deformability characteristic are of prime importance [1]. Parametric correlations are very significant part of rock/soil mechanics study since inception. In some cases they are necessary, as it is difficult to measure the parameter directly, and in other cases it is desirable to ascertain the results with other test through correlation. The correlations are normally semi empirical, based partly on mechanics or purely empirical, based only on statistical analysis. Determination of parameters e.g. compressive strength, RMR (Rock Mass Rating) or deformability of a rock material is time consuming, expensive and involves destructive test. A reliable predictive model could be obtained with the help of various AI techniques to correlate the various parameters, they will be very useful for at least the preliminary stage of designing a structure. The use of empirically obtained parameters may not be so useful & reliable for engineering projects. However, these data would be very valuable for at least the primary stage of designing a structure, when the data joined with interpretation is based on engineering experiences. ”The only thing known with certainty is that this material will never be known with certainty” in case of materials of natural rocks [2]. In recent years, some methodologies in artificial neural network (ANN), fuzzy systems, and evolutionary computational techniques have been successfully combined and new techniques called soft computing or computational intelligence have been developed. These techniques are attracting more and more attention in several engineering research fields because they can tolerate a wide range of uncertainty. Since the early 1990 ANN techniques have been applied to almost each and every problems of underground mining. This technique has been successfully implemented in blasting [3], dams [4], earth retaining structures [5], environmental geotechnics [6], ground anchors [7], liquefaction[8], pile foundation[9], rock mechanics[10], site characterization[11], shallow foundation[12], slope stability problems [13], soil properties and behavior[14], tunnel and underground openings and workings[15].Blast induced ground vibration have been modeled with the help of ANN by some researchers[16],   The flow chart depicted in figure 2.1 is for the design of underground structure in rock [17].

DESIGN OF UNDERGROUND EXCAVATIONS WITH SUPPORTS

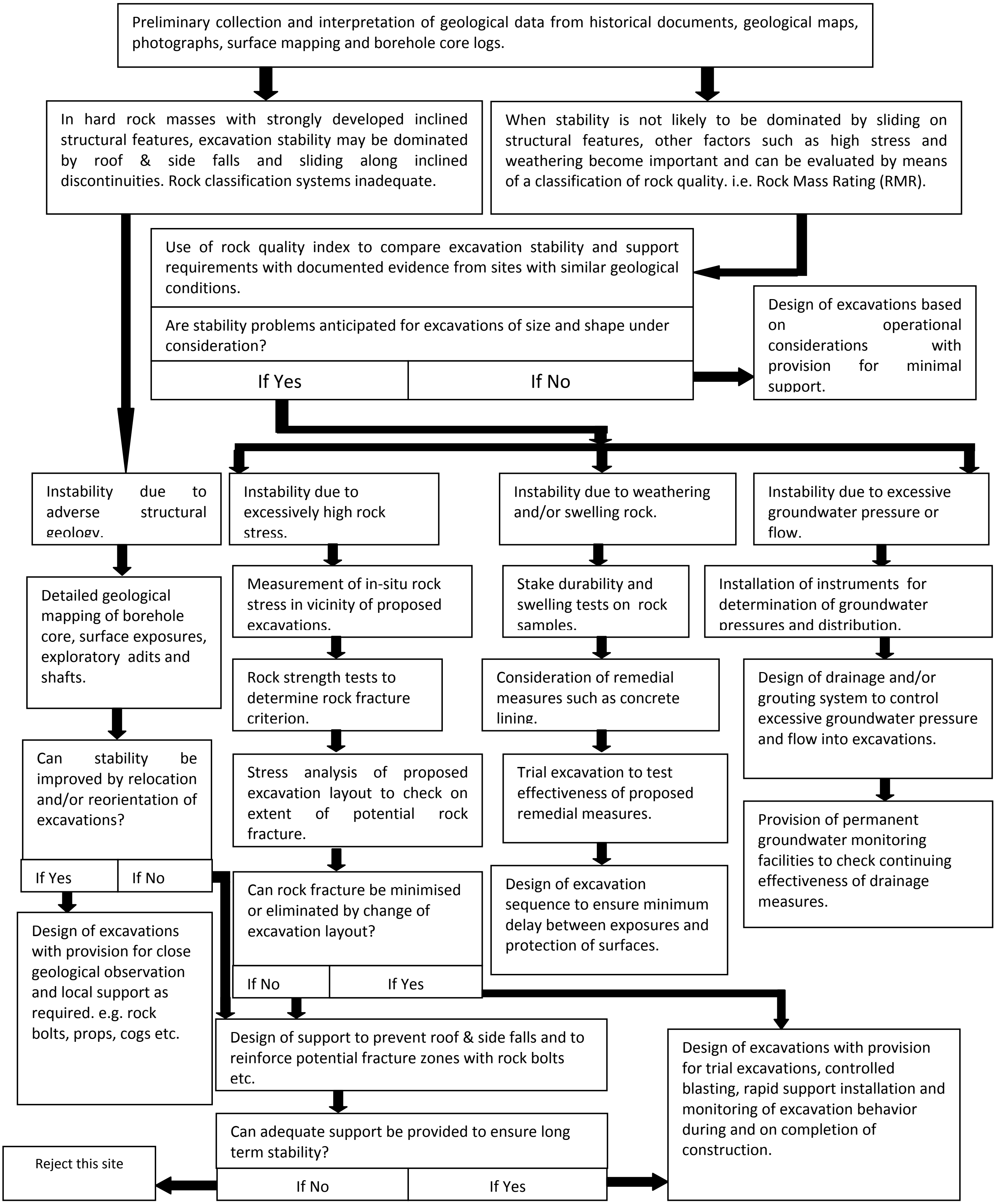


Figure 2.1 Design of underground excavation with supports

2.2 Geo – Mechanics of Mine Support Systems in UG Mines

Bord and pillar method of mining is still one of the widely accepted practices in India to extract coal from the underground mines. In this method, coal (20-30%) can be extracted during development in seams, which can be developed to a maximum width (4.8m) and height (3m) (18). Due to complex geometry of developed panels and complicated procedures of pillar extraction (Splitting & Slicing), rock mechanics and strata behavior in bord and pillar depillaring working are different from other common underground excavation methods of coal. Importantly, two empirical approaches are being used for design of mine support system for bord and pillar depillaring operation[17,18] .

CMRI Geomechanical classification (CMRI-RMR) system: CMRI-RMR system is used for design of mine support system in roadways during development stage of the mine. To determine the RMR of the mine roof rock in existing galleries and split in depillaring five parameters i.e. Layer thickness, Structural Features, Weatherability (Ist cycle slake index) , Compressive strength, Ground water and RMR are used.

NGI(Norwegian Geotechnical Institute)Rock Mass Quality Classification: NGI-Q system is used for design of support during depillaring. Where Q is determined using the following relationship:

$$Q = (RQD/J_n) \times (J_r/J_a) \times (J_w/SRF) \qquad (2.1)$$

Where RQD= Rock Quality Designation

J_n = Joint set Number

J_r = Joint roughness number

J_a = Joint alteration number

J_w = Joint water reduction number

And SRF = Stress Reduction Factor.

As no borehole core of immediate roof is available the RQD needed in NGI-Q system is determined from joint volume (J_v) i.e. number of joints per cubic meter of rock mass from the following relationship:

$$RQD = 115\text{-}3.3J_v \qquad (2.2)$$

<u>Estimation of rock load in depillaring areas:</u>

Rock Load in Galleries and Split

Rock Load (t/m^2) in the galleries and splits using empirical relation of CMRI-RMR System

$$\text{Rock Load} = B \text{ X } D\ (1.7 - 0.037 \text{ X } RMR + 0.0002 \text{ X } RMR^2) \qquad (2.3)$$

Where B = Width of galleries split

D = Average Rock Density

RMR = Rock Mass Rating

Rock Load at Junction

Rock load at junction of galleries and split in depillaring areas using empirical relation of CMRI-RMR System:

$$\text{Rock Load} = 5 \text{ X } B^{0.3} \text{ X } D\ (1\text{-}RMR/100)^2 \qquad (2.4)$$

Rock Load in Slices and Goaf Edges

Rock Load in slice and goaf edge estimation using NGI-Q system from the following empirical relation:

$$P = 2/3\ (J_n^{1/2}/J_r) \times (5Q)^{-1/3} \quad (2.5)$$

2.3 Mine Supports in Underground Mines

In many circumstances, our basic understanding of soil and rock characteristics still falls short of being able to predict how the ground will behave. Cause-wise analysis of underground mine accidents states that roof falls continue to remain the single largest killer. Ground control is an 'imprecise' area of engineering due to the fact that we are dealing with a material produced by nature (the ground). Proper support selection is one of the important aspects of mine design and planning. For stability of any underground excavation proper design of support is essential. In bord and pillar mining main roadways, galleries, junctions and goaf edges are required to be supported in development of mine. In depillaring operation i.e. complete extraction of coal splits and slices are supported in addition. There are various types of mine support equipments designed as per rock load which varies according to geo-technical characteristics of respective mines as depicted in table 2.1. Some of the support system with optimum resistance capacity of rock load which are readily used in mines are [18]:

TABLE 2.1 Types of mine supports

Sl.Nos	Support equipments	Measurements	Capacity (t/m^2)
1.	Pit Prop	About 3 m long ,made of mild steel pipe (100 diameter,5mm wall thickness,0.5-1.0 long)	20
2.	Timber chock	a) Seasonal round timber cogs (1.2x1.2 m area ,3m high) b) Flat chock (1.0mx1.0m) made of slippers (100x75mm section)sawn from the seasonal hard wood.	30 30
3.	Steel chock/cogs	a)Made of steel cog stool (0.9x0.9x0.9m) fabricated from box steel pipes (48.5x48.5 mm section ,3.65mm wall thickness) following any standard accepted design b) Made of steel cog stool (0.9x0.9x0.9m) fabricated from box steel pipes (48.5x48.5 mm section ,3.80mm wall thickness) following any standard accepted design c)Made of steel cog stool (0.9x0.9x0.9m) fabricated from box steel pipes (72.0x72.0 mm section ,4.5mm wall thickness) following any standard accepted design	30 40 50
4.	Rock bolt	1.5 mm long ,full column cement or resin grouted made of ribbed tor steel (20-22mm diameter.	8
5.	Hydraulic prop	Telescopic type ,made of two steel pipe (concentric)	40
6.	Friction Prop	Telescopic pipe, made of two steel pipe (concentric)	40
7.	Screw prop	Made of steel pipe having threaded part on the outer body with lead screw	20

In addition to the above mentioned pit prop, SHS prop, Adjustable cross bar support and steel cogs of various sizes of the capacity as mentioned above are used in mines.

2.3.1 Preloading of Standing Support

A critical safety equipment for all underground excavation is intrinsic and thus standing support systems is required. Several new mine support systems have been developed in recent years for hard rock applications. These include prestressing equipments like yielding support, improved cribs, and free standing supports having mechanism to apply setting load into it. Various standing support systems like prop-type systems have been designed for hard rock applications with seismic loading conditions to accept setting load. The prestressing, using water-filled cells, creates an active setting load upon installation and is considered essential to maintain proper support during and after the blasting of the mine faces [19]. Heavy seismic activity is present in the mines and the prestressing units can provide some energy absorption capability to help preserve the integrity of the support [19].

For tabular deposits [19], various types of standing supports and cementitious rock bolting are used with mining methods such as longwall mining, one of the other methods of coal mining. Actually, timber props and wooden cross members were some of the earliest forms of standing support. Particularly the preloading can be beneficial to install support that commonly uses a variety of timber posts and headers. A wide variety of prop-type supports has been developed that provide both non-yielding and yielding characteristics. Standing support systems use has also been limited due to stability problems at operating roof heights beyond 2.5 m and also due to space for other mechanisation. Here too, improvements in mine roof support technology have been made in recent years, including improvements in timber crib systems, newly invented steel yielding prop and also heavy capacity steel chocks/cogs which have operated in heights up to 4 m. In addition to these there are some other yielding prop like hydraulic prop, friction prop etc. which are being used wherever required in some countries.

The benefit of preloading or applying setting load externally to the standing support systems is to change the state of stress in rock formations or to provide confining forces that resist movement along fracture planes that has been commonly used in mining engineering fields for many years. Applying higher setting load helps in reducing bed separation and improve strata control. Pretensioning of long cable bolts or rock bolt, which are a common form of support in hard rock mining, has been particularly difficult because mechanical means typically apply a torque to the cable strands/rock bolt creating a spring back effect that reduces the tension after the external torque is withdrawn. This has been applied to preloaded prop support systems that bridge the mine opening from the floor to roof as per characteristics of the rock [1,20]. Historically, these supports are particularly passive supports that generate their load carrying capacity only through the closure of the mine opening, i.e. through roof movement. For wooden supports and other yielding support this can mean a few centimeters of convergence will occur before the support generates significant load resistance. As per many workers including Peng et al. [21], the relationship between convergence and setting load may be shown by a curve depicted in Figure 2.1(a). When the setting load is low the ability of the support to resist roof converengence is less. Conversely, the ability of the support to resist the roof converengence is high and lesser converengence is expected if the setting load is high. Peng et al.[21] recommends high setting load in a roof consisting of strong strata to support the large strata weight from the overhanging rock beam. Application of a prestressing / preloading with the help of hydraulic jack can create an immediate active force against the mine roof and floor.

These units can be used to apply up to 12 tons setting load or even more. The rigid support like pit prop, wooden prop and steel cog are rigidly fixed to the roof with preloading of about 8 tons given by wooden wedge in between floor and the bottom of the pit prop and wooden sleepers in between top of the wooden prop and steel cog and roof respectively. It can also be equipped with headboards to further distribute the roof load to the mine roof. In addition to improving roof control, prestressing of these props can be beneficial in ensuring that the props are able to withstand ground reactions and air blast during blasting when used in the immediate vicinity of the face. A purely passive support or one that is only lightly preloaded from wood wedges is likely to become dislodged during nearby blasting operations.

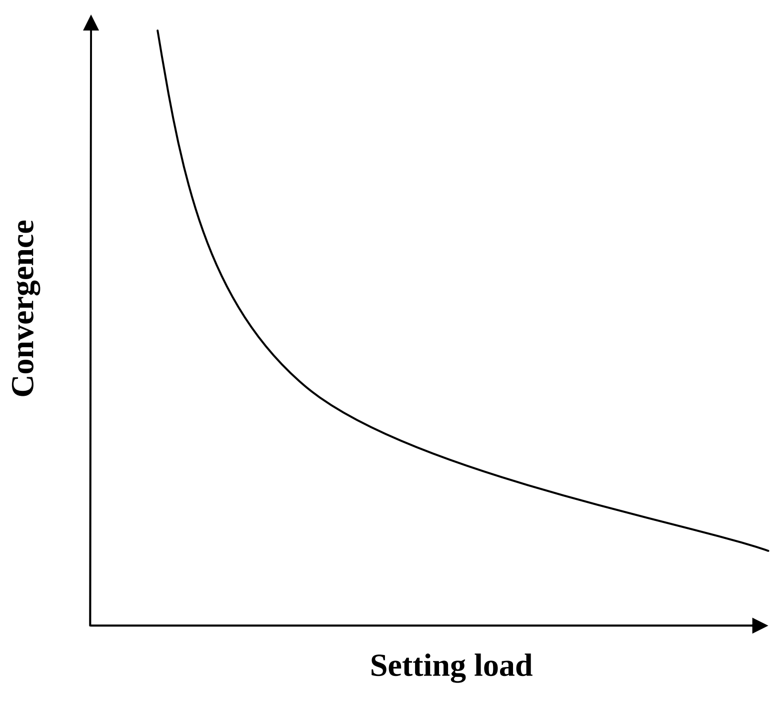


Figure 2.1(a) Influence of setting load (Peng et al.[21])

2.3.2 Various Mechanism of Preloading of Standing Support

Recently, an inflatable metallic bladder has been developed that can provide a direct axial pretensioning force to the cable / rock bolt through hydraulic pressure without inducing any torque into the bolt. The inflatable metal bladder is placed between the roof bolt plate and the head of the bolt. It can provide up to 10 tons of preload. In this technique a quick connect hose is placed on the bladder and filled using air or hydraulic pressure. Another design of these preloading bladders can also be enlarged to fit a variety of crib or pack type supports. In this system, two flat sections of metal sheets are welded along the perimeter to create a large cell that with relatively little water pressure can create large preloads. In South African gold mines, these systems are used on timber packs. In addition to providing a substantial active force to the mine roof, these devices can be beneficial in prestressing the support devices to remove any initial softness due to construction whereby timber dimensional tolerances or some other issue create a disjointed structure Barczak. et al.[1]. In addition to the above preloading mechanism there are hydraulic jack (single and twin jack) and power pack which can provide upto 10 ton of preload to the friction prop and hydraulic prop respectively. In pit prop and even steel cogs the approximately same load can be provided with the help of timber wedge or timber packing.

2.3.3 Pullout load of rock bolt support

Pretensioning of rock bolts and cable bolts is performed by tightening the end nut to a predetermined torque. This has been an effective means of pretensioning conventional roof bolts. This approach is more problematic with cable bolts since the wire strands twist when the torque is applied and can untwist when the torque is removed resulting in a loss of the achieved tension. Tightening of nuts to achieve pretension is also subject to significant frictional loss that further reduce the efficiency of this approach[1]. The efficacy of the rock bolts depends upon the many potential factors like quality of cement grout/resin and more importantly ground behavior. As per regulatory authority in India the pullout test is necessary to know the perfection of grouting of roof bolts. Pullout test is recommended empirically 3 ton after 30 minutes and 5 ton after 90 minutes for 22mmx1.5m TMT bar.

2.4 Mine Support Parameters

The stability of an underground opening is influenced by many factors / parameters such as intact rock quality & characteristics, discontinuity pattern, discontinuity aperture, in-situ stress, hydraulic conditions, etc. [22]. The interactions among these factors are very complex, they act on rock behavior simultaneously and it is very difficult to analyze these factors simultaneously with a traditional methods & approach [23]. For evaluation of preload on standing prop or required pull load on rock bolting there may be some more factors to be considered. If there are enough data for learning, the AI techniques will be an ideal tool for this kind of problem. A few parameters that contribute in optimization of preloading on prop or pull load on anchorage:

- Rock type
- Roadway span;
- Depth of roadway;
- Uniaxial strength;
- *RQD* - rock quality designation
- J_n - joint set number
- J_r - joint roughness number

- J_a - joint alteration number
- J_w - joint water reduction factor
- *SRF* - stress reduction factor
- Rock density.
- *RMR* – Rock Mass Rating
- Seam thickness
- Width of gallery
- Working height at face
- Diameter of drilled hole in the roof
- Depth of drilled hole
- Charge per hole at the working face
- Respective distance of prop or rock bolt from the face

2.5 Neural Network Techniques

2.5.1 Introduction

The mammalian nervous system i.e. the human brain has been the source of inspiration for decades of research for a computational model, which is based on learning from experience rather than on hard-coded programming. The human brain, central to the human being nervous system, is generally understood not as a single neural network but as a network of neural networks each having their own architecture, learning strategy, and objectives. The massive parallel processing characteristic of the human brain and the deriving advantages of this structure always attracted the attention of the researchers especially in the field of computing

[24]. Typical biological neural networks, regardless of their functions and complexity, are composed of building blocks known as neurons (Fig. 2.2) [25]. The minimal structure of a biological neuron consists of four elements: dendrites, synapses, cell body, and axon.

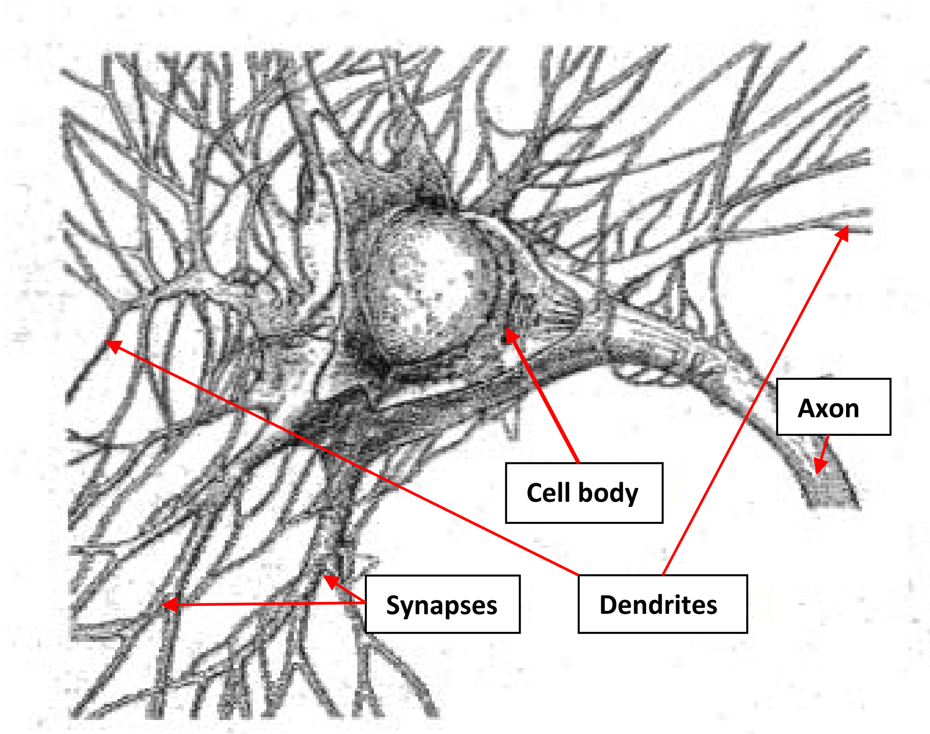


Figure 2.2 View of a typical neuron (Stevens et al. [25])

Neural networks are a branch of Artificial Intelligence techniques ", besides Case-based Reasoning, Expert Sytems, and Genetic Algorithms. Neural networks are able to identify similarities in inputs, even though a particular input may never have been seen previously. This property allows for excellent interpolation capabilities, especially when the input data are noisy [25]. Neural network with their excellent ability to derive a general solution from complicated or imprecise data can be used to extract patterns and detects trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an “expert” in the particular category of information it has been given to analyse. Thus, the artificial neural network can act as an expert. The particular network can be defined by three fundamental components: transfer function, network architecture, and learning law [26] as shown in following figure 2.3

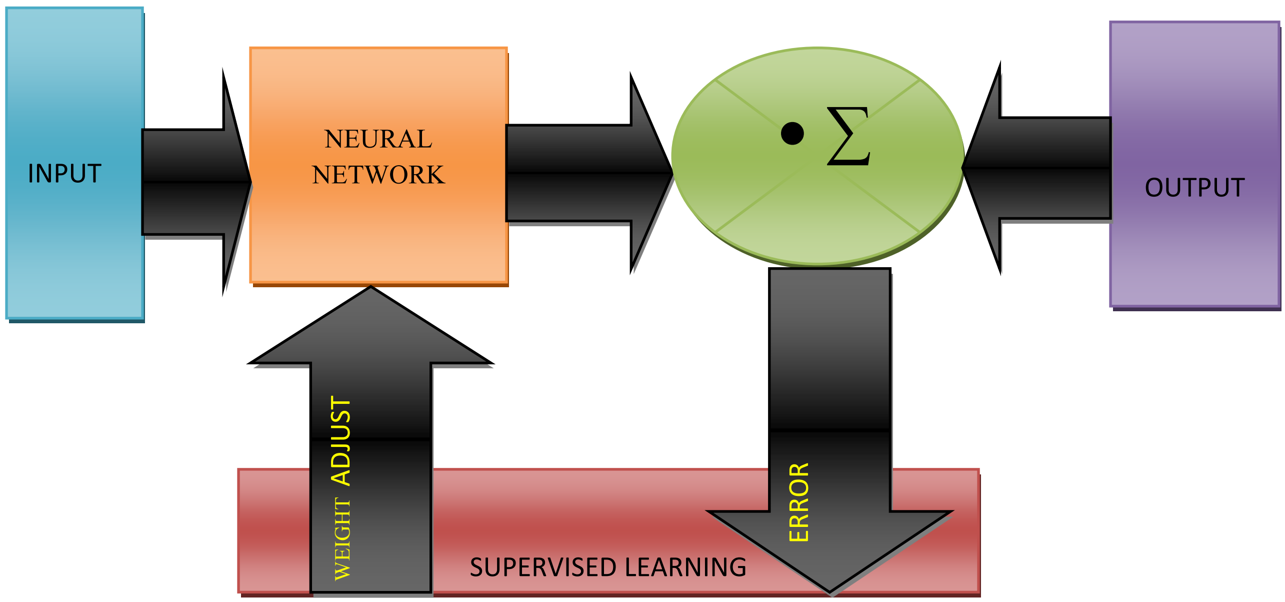


Figure 2.3 Supervised learning

A neural network is a parallel - distributed processor comprising several simple computational units known as neurons [24]. Figure 2.4 shows the model of a neuron. A neuron model can be identified by three basic elements.

- A set of synapses or connecting links, each of which is characterised by a weight or strength of its own. Specifically, a signal x_j at the input of synapse ‘j’ connected to neuron ‘k’ is multiplied by synaptic weight w_{kj}.

- An adder for summing the input signals after they have been weighted by the respective synapses of the neuron.
- An activation function is used for transforming the result of the adder and limiting the amplitude of the output of a neuron. In General, the normalized amplitude range of the output of a neuron is given as the closed unit interval [0,1] or alternatively [-1,1]

Mathematically, neuron k can be described by two following equation,

$$u_k = \sum_{j=1}^{p} w_{kj} x_j \tag{2.6}$$

$$y_k = \varphi(u_k) \tag{2.7}$$

where $x_1, x_2, \ldots, x_p$ are the input signals; p is the number of input signals; $w_{k1}, w_{k2}, \ldots, w_{kp}$ are the synaptic weights of neuron k; u_k is the output of the adder; φ (.) is the activation function and y_k is the output signal of the neuron. The activation function, denoted by φ (.), defines the output of a neuron in

terms of the activity level at its input. In this research work the activation function that is used is Sigmoidal Function shown in Figure 2.5 [27]. A neural network resembles the brain in two respects:

• Knowledge is acquired by the network through a learning process.

• Inter-neuron connection strengths known as synaptic weights are used to store the knowledge.

The procedure used to perform learning is called a learning algorithm, the function of which is to modify the synaptic weights of the network in an orderly fashion so as to attain a desired design objective.

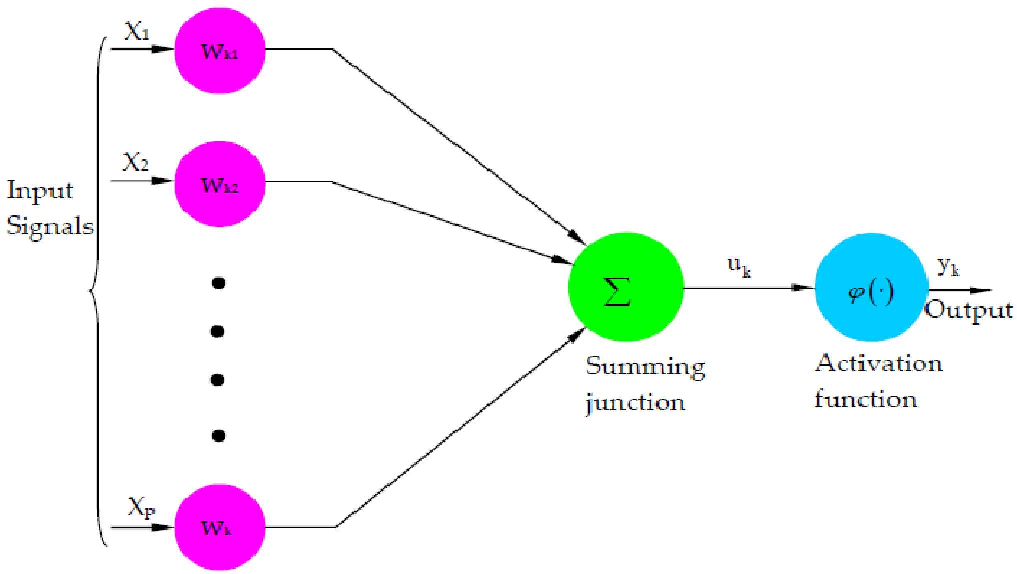


Figure 2.4 Model of a neuron

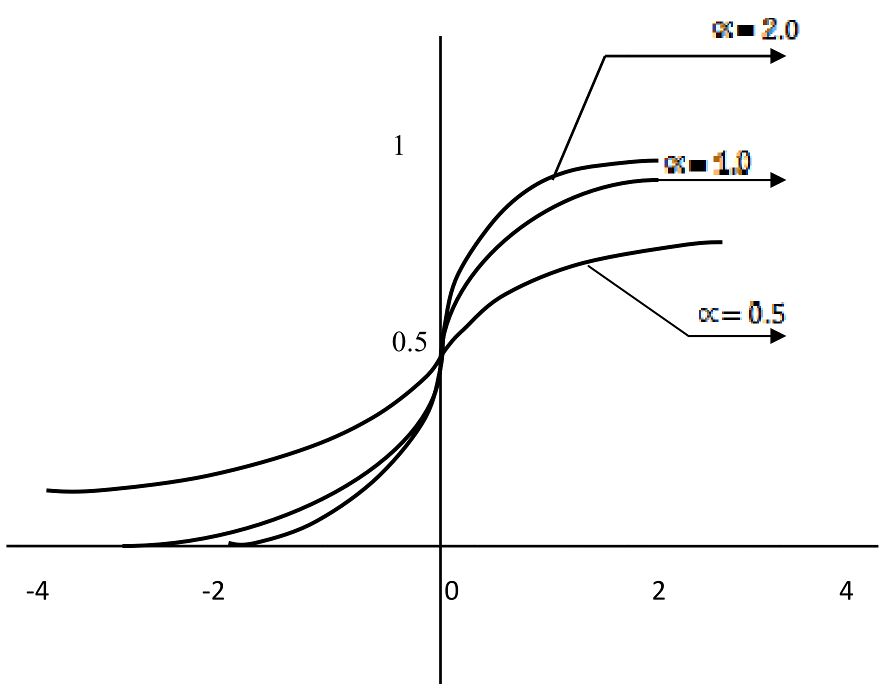


Figure 2.5 Sigmoidal function (Rajasekaran et al.[27])

2.5.2 Neural Network Architecture

Feed forward back-propagation neural network (BPNN) architecture is adopted due to its appropriateness for the identification problem. Pattern matching is basically an input/output mapping phenomena. The closer the mapping, the better the performance of the network [16]. A typical network architecture[28] having two input layers, first hidden layer having 28 neurons, second hidden layers having 28 neurons and one output layer has been shown in Figure 2.6 for ore grade/reserve estimation .

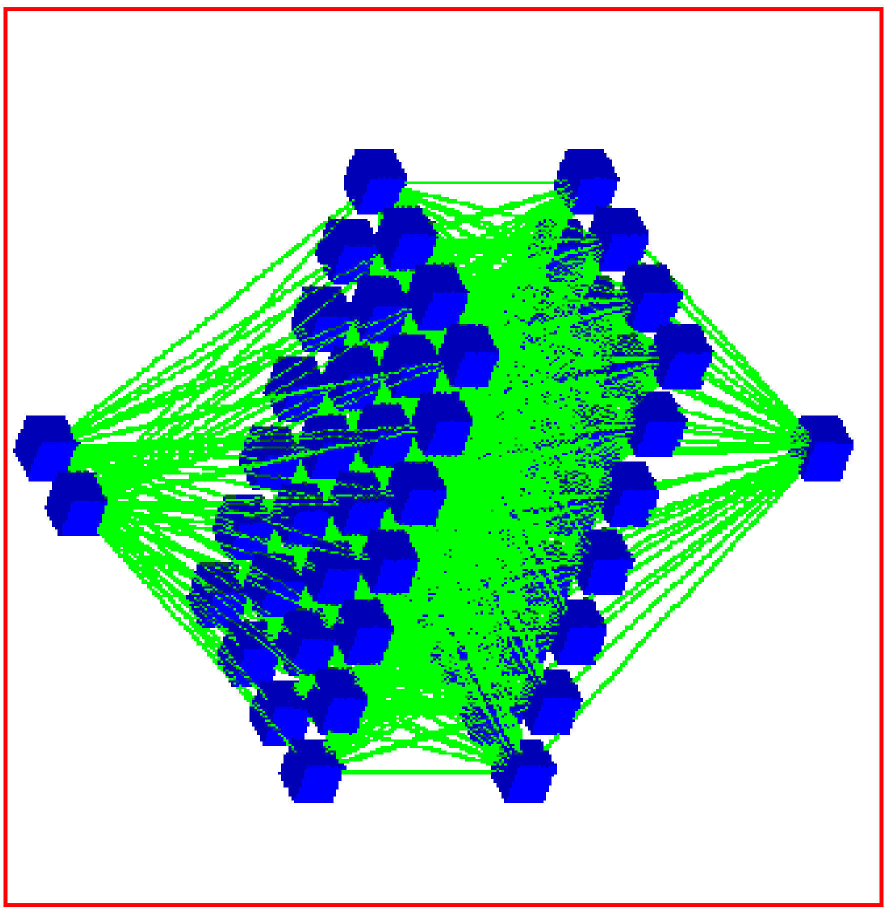


Figure 2.6 ANN architecture (Wu et al.[28])

2.5.3 Backpropagation

Back-propagation neural networks (BPNN) are the most versatile and widely used and well understood of the supervised learning algorithms. The back-propagation neural network necessarily has an input layer, an output layer and atleast one hidden layer. During training a back-propagation network, it adjusts automatically the connection weight between neurons based on some kind of learning laws. If the error of the network output is within our permissible limit, the training process stops, otherwise training continues.

There are three main phases in implementation of ANN model [29] .They are

1. Learning Phase: Learning is the process of training of adopting or modifying connection weight in response to stimuli being presented at the input end and ,optionally the output.
2. Testing Phase: This is the critical verification stage of data for the particular model development. Before training a model, data are divided as training data and testing data.. When the model is completed using the training data , it is tested on test data set which it has never come across.
3. Deploying Phase: When the model is trained and tested ,it is ready to solve any new problems. However, care must be taken that the trained model applies only to systems for which the training data are representative.

Figure 2.7 shows a flow chart of neural network training for weight determination [30]

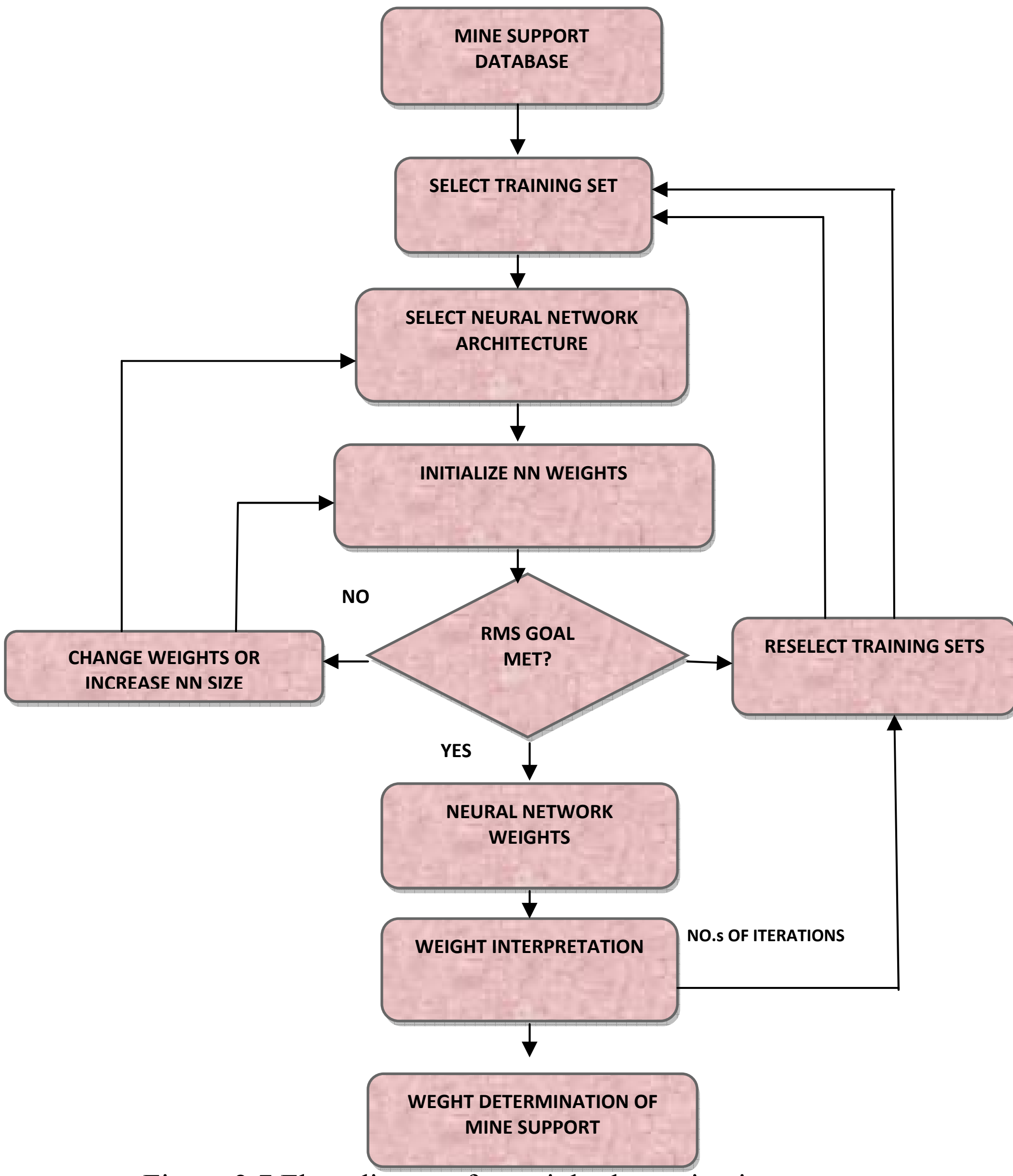


Figure 2.7 Flow diagram for weight determination

The popularity of BPNN has been a major factor in the resurgence of neural network techniques. Backpropagation [31] is a systematic method for training multi-layer neural networks. Despite its limitations, backpropagation has dramatically expanded the range of problems to which artificial neural networks can be applied, and it has generated many successful results. BPNN has been successfully used as a mapping and prediction tool in the geo-mining engineering field. Its application as a tool in underground mining is proven [31].

Deficiencies of the BPNN Model:

Despite its much popularity and versatility, BPNN often have some deficiencies in its learning speed and failure to guarantee its convergence within a minimum time. The troublesome long training process results from non-optimum learning rate. In addition, there is no well-defined algorithm for determining the optimal number of hidden nodes. Therefore, trial and error is the only way to arrive at a suitable learning rate and the optimal numbers of hidden nodes. Outright unsuccessful training may occasionally be encountered resulting from the network paralysis and convergence at local minima instead of global minima [32]. Even then, still it is much accepted globally.

2.5.4 Neural Network Applied in Underground Mines

Artificial Intelligence (AI) tools have been in use for few decades in a number of mining related applications. Expert and knowledge based systems, probably are the most popular AI tools, have found their way into a number of computer-based systems supporting everyday mining problems as well as production of mining equipment. In recent years, AI has provided tools for optimizations and equipment selection, problems involving large amounts of information that humans cannot easily cope with in the process of decision-making. These AI systems together with an ever increasing number of sophisticated purpose-built computer software packages have created a very favorable environment for the introduction of yet another most effective AI tool, the Artificial Neural Networks. Kapageridis et al. [24] stated in the ‘90s that various mining industry applications can be solved using ANN based systems. Exploration and Resource Estimation are the most important of the mining problems and there are more ANN systems targeted to this field of mining. The grouping as well as the selection of the examples was purely based on the relevance of the applications to the subject of this thesis.

Neural network technology has been applied to various real world problems with remarkable success in diverse area, such as pattern recognition [33], pattern classification [34, 35], financial applications [36], decision analysis, and optimization and so on. In the geo-engineering and mine industry its application have been bit slowly, but work have just began a decade before [29]. Underground excavation is one of the difficult and hazardous activities. Efficiencies of excavation and associated safety depend upon many factors but solely on the unpredictable rock behavior and its characteristics. Rock behavior vis-à-vis the stability of underground opening depends on various factors such as the grain size, mineral composition, aspect ratio, form factor, loading geometry, etc., is controlled by many different factors which have varying level of influence. It is very difficult to identify the relative effect of each factor with traditional old methods, such as structural analysis and statistical approach. In the past mathematical models were developed to simulate the observed behavior for rocks used for phenomenological evidence and human reasoning. However, the resulting mathematical models are often limited in their ability to account for the effects of these variables because of the restrictive and at times wrong assumptions.

Some researchers have estimated the ground subsidence with BPNN [37, 38]. Backpropagation neural network uses sigmoid function basically to determine weights of factors. Therefore each value of all factors were rescaled from 0.1 to 0.9 then inputted into backpropagation algorithm. Spatial surface of subsidence was shown in figure 2.8.

Figure2.8 Spatial surface of subsidence area (Kim et al. [37])

A very typical neural network architecture has been shown in figure 2.9 having 12 nos. of input data of mine parameters in input layer and 4 nos. of hidden layers containing 30,14,7,4 nos. of neurons respectively and one output layer.

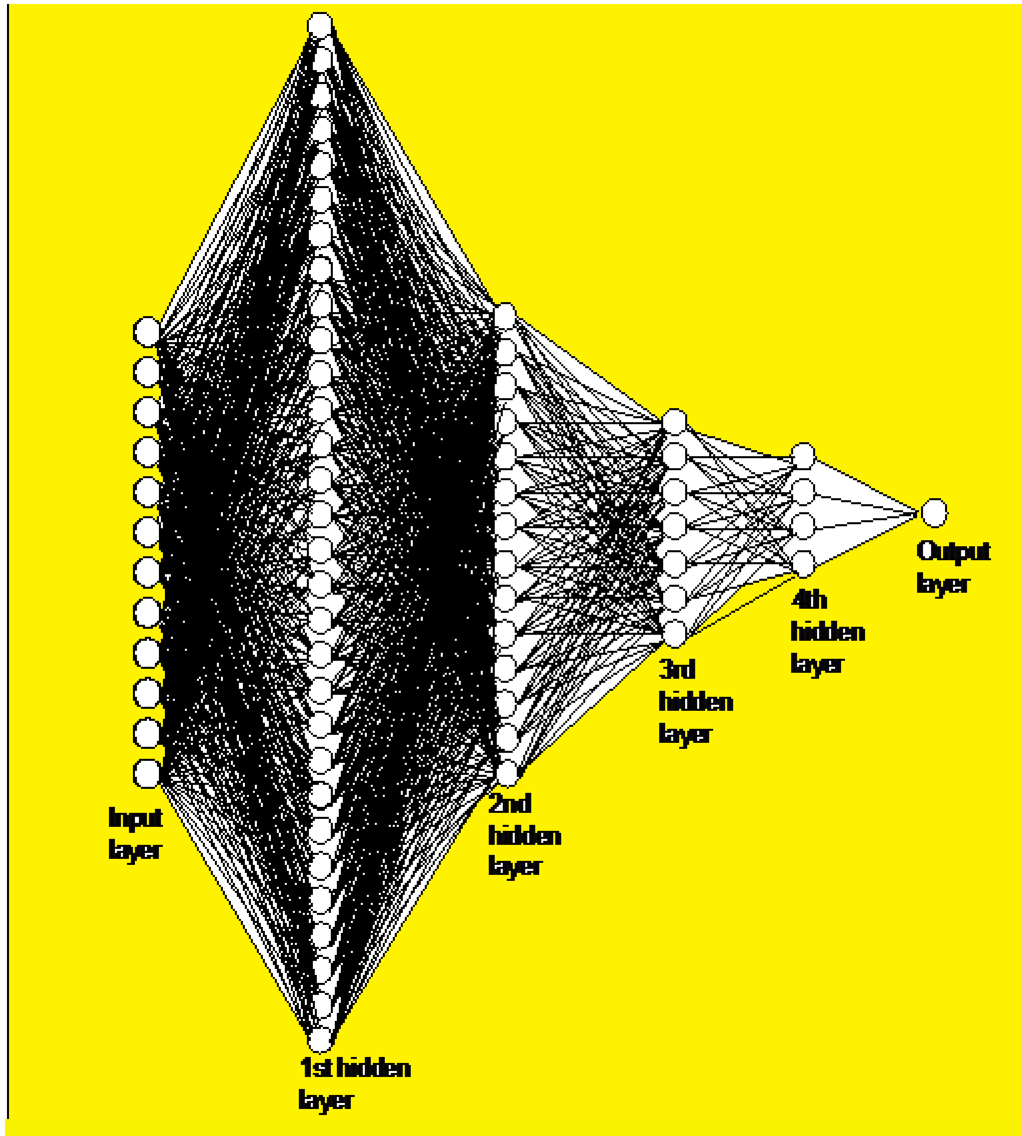


Figure 2.9 Neural network architecture

To enhance the safety of underground mines researchers [37] have applied neural network technology to the classification of mine roof strata in terms of relative strength. That is, measurement taken while a roof strata is being drilled can be used to compute the specific energy input and convert these data to suitable scale feature. Then neural network was used to classify the strata.Compression wave velocity and anisotropic behavior of rock are two such properties which help to understand the rock response under varying stress conditions.They also influence the failure mechanism of rock [39].There are various methods to determine these parameters,but Neural Network technique seems to be very well suited for typical geotechnical problems. The mining industry depends totally upon empirical analysis for design and prediction of geotechnical activities.Neural networks are computer programs that use parallel processing, similar to the human brain,to analyze data for trends and correlation. Artificial neural network were also applied in the mining industry for rockburst prediction and stope dilution estimation at the Ruttan Mine [40].Blast induced ground vibration and frequency was evaluated and predicted by rock properties , blast design and explosive parameters as input data using the neural network technique[16] .Some researchers[1] have predicted unconfined compressive strength and elasticity modulus of gypsum using this technique and a correlation could be established. Longwall mining technique is one of the two basic methods of underground coal mining, the other being Board & Pillar mining.ANN technique were applied to estimate the front leg pressure [41]. In addition to standing support there is another prominent and globally accepted support system i.e. rock bolting reinforcement for ground anchors. An attempt has been made by one of the researcher [42] for prediction of pullout capacity of marquee ground anchor with the help of neural network technique. Deb et al. [43] have monitored and recorded the leg pressure data from all shields of a longwall face. A computer algorithm was developed to detect peak pressure or periodic roof weighting from these pressure data. The intensities and location of periodic roof weighting was further estimated using artificial neural network for forecasting of forthcoming shield pressure. Yang et al. [22] have analysed the different rock parameters for underground mines hierarchically by using neural network technique. Debelle et al. [44] have dealt with the methods of characterizing mine roof and floor for improving the mining environment. This research investigated using a neural network to classify rock strata based on the physical parameters like thrust, torque, penetration rate, rotational velocity etc. of a roof bolting drill. Deng et al.[45] have used neural network technique in pillar design for a copper mine in China. Kolay et al. [46] have used ANN to predict the compression index of some tropical soil with 3 layered feed forward back propagation. They have also found out the maximum nos. of neurons in hidden layer. Some researcher[47] have used ANN for the prediction of non-linear behavior of vertically loaded piles based on the results of Standard Penetration test (SPT) data. Verma et al. [48] have described to assess'Remaining Useful Life of Lubricant (RULL)' with the help of ANN. The researchers mentioned it a good technique other than the statistical methods to determine the RULL. Mukherjee et al. [49] have shown the extension neural network based recognition methods which can identify the safety status pattern of the underground coal mines accurately with shorter learning time and simpler structure.

2.6 Fuzzy Logic Techniques

2.6.1 Introduction

In the design of underground constructions, it is very difficult to take into account the inherent variability of rock mass using the current rock mass classifications. One of the prime means of improving rock mass classification is by accounting for variations in the individual parameters using fuzzy mathematics [50]. The fuzzy set was first introduced by Zadeh et al. [51] as a mathematical way to represent linguistic vagueness. In case of a classical set, an element belongs to, or does not belong to, a set. Contrary to crisp or (ordinary sets) fuzzy sets have no definite precise or sharp boundaries. In the crisp set A the membership or non- membership of an element x is represented by the characteristic function μ_A of A, defined by

$$\mu_A(x) = \begin{cases} 1 & if\ x \in A \\ 0 & if\ x \notin A \end{cases} \tag{2.8}$$

Since fuzzy sets states vague concepts based on the premise that their elements used are not numbers but belong to word descriptions or linguistic categories ,an element of this set naturally belongs to a linguistic category with membership values from the interval [0,1]. Mathematically, the fuzzy set A will be

$$A = \{ x, \mu_A (x) | x \in U \} \tag{2.9}$$

Where U refers to the universe of discourse defined for a specific problem and μ_A (x) is the membership degree of variable x that is defined as

$$\mu_A (x) \rightarrow [0, 1] \tag{2.10}$$

This type of membership function is characterized by a smooth and clear transition from ”belonging to a set” (1) to ”not belonging to a set” (0) and gives fuzzy sets flexibility in modeling based on linguistic expressions of engineering practice (such as ”fairly hot surface”). The fuzzy logic, a generalization of classical set theory, is useful to explain the imprecise information by selecting a suitable membership function. The process of generating membership values for a fuzzy variable using membership functions, or the process of converting a crisp value to a fuzzy value is defined as a fuzzification [52]. The shape of the membership functions can be either linear (trapezoidal or triangular) or various forms of non-linear, depending on the nature of the system being studied. This figure 2.10 shows the linguistic representation of various membership functions.

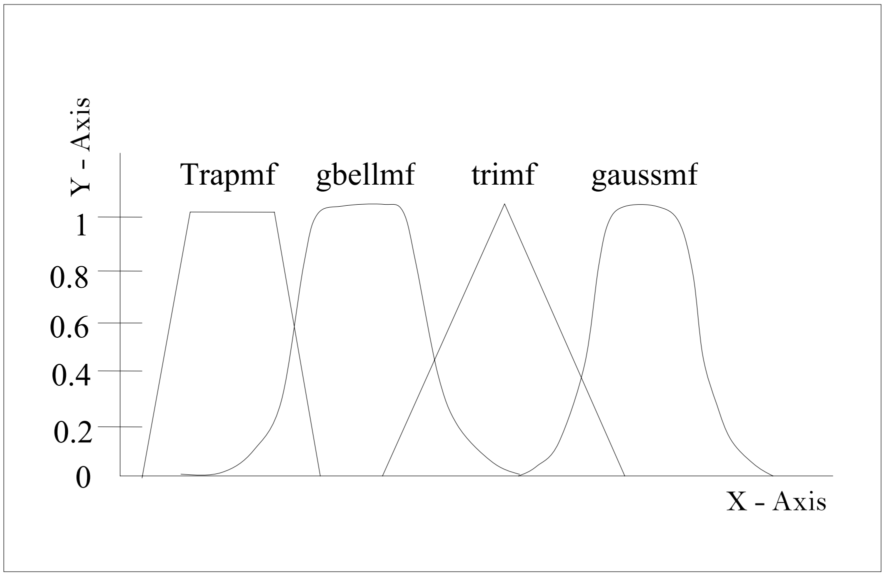


Figure 2.10 linguistic representation of various membership functions

Fuzzy set theory can also be used for developing rule-based models which combine expert knowledge or experiences and numerical data in a transparent way that closely resembles the real world. This theory presents a systematic calculus to deal with linguistic terms, and it performs numerical computation by using linguistic labels stipulated by membership functions. Additionally, fuzzy ''if–then'' rules form the key component of a Fuzzy Inference System (FIS) that can effectively model human expertise in a specific application [53]. There are primarily two fuzzy modeling algorithms are available to predict the model i.e. a rule-based fuzzy model based on one developed by Mamdani et al.[54], and the other is a parametric-based fuzzy model based on one developed by Sugeno et al.[55]. The main components of the model were fuzzy inference, fuzzy sets for input/output variables, and fuzzy if-then rules. The modeling procedures for both algorithms included [56]: The modeling procedures are:

- Identification of input and output variables
- "Fuzzification" of input and output variables
- Multivariable linear regression
- Fuzzy if-then rule statements
- Modeling results (Defuzzification)
- Model validation.

The method of fuzzy modeling has been shown in figure 2.11 below.

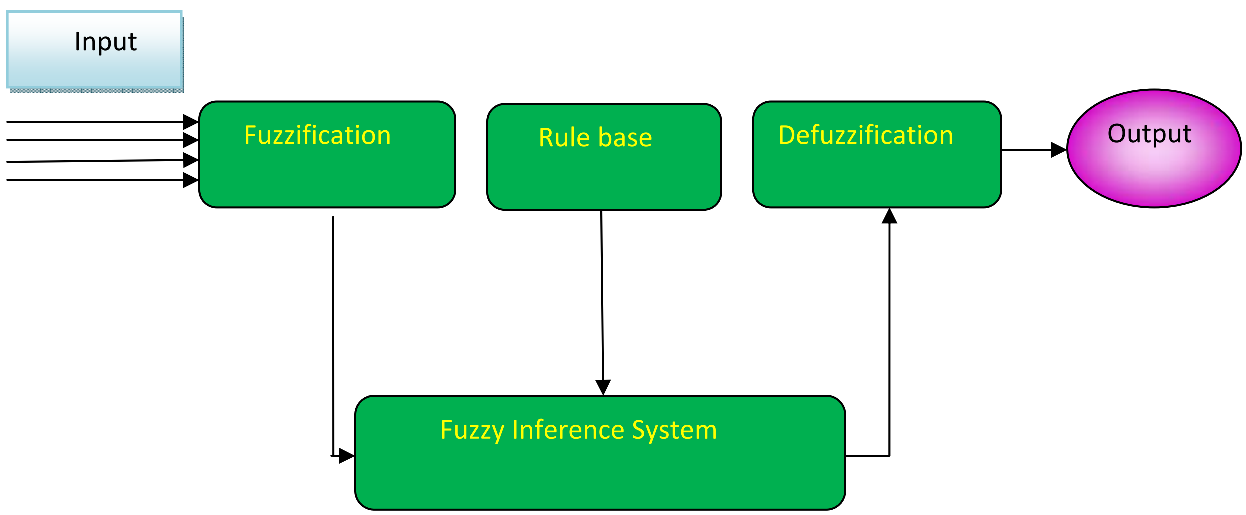


Figure 2.11 Process of fuzzy modeling

2.6.2 Fuzzy Logic Applied in Underground Mines

For nearly two decades the use of fuzzy control and fuzzy set theory has expanded rapidly into virtually all areas of the industry including geology, mining, metallurgy, and control of environmental pollution, land slides, soil characteristic and many more and in optimization. In mining industry fuzzy logic can be used for:

- Underground mine ventilation and environmental quality control
- Mineral processing control
- Mine risk assessment
- Mine safety and warning system (including support system, blasting of rock mass, subsidence etc.)
- Mine design system
- Underground mine roof drilling
- Rock mass characterizations

Kim et al. [56] has developed a model using fuzzy logic to predict TBM (Tunnel Boring Machine) utilization—the percentage of shift time during which tunnel boring operations occurs. With its potential to predict the TBM advance rate, this modeling technique has been proved a useful tool for estimating the excavation time and cost for project bidding and planning purposes. It is also an important parameter for evaluating tunneling system efficiency. Hillar et al. [50] have discussed the rock mass behavior which is influential parameters for underground excavation work. Oberste et al. [57] have discussed and developed a calculation procedures by means of fuzzy logic components, expert rules and generate results that correlate to the distributed and uncertain nature of the ground behavior. Cagnoli et al. [58] stated that fuzzy logic is probably a simple and most effective tool to model volcanic systems because it enables a mathematical formalization of ill defined problems and geological knowledge is typically imprecisely defined. Fuzzy logic enables more flexible classifications because it describes sets whose members belong to them to only some degree. There are many examples of geological objects that do not fit well into traditional classifications because they have their own characteristics to only some degree, such as rock properties. Bardossy et al.[59] discussed the critical exploration problem of the completeness of an exploration project . It is of crucial importance for making exact decision to start or to give up a mining investment, or to continue the exploration to get complementary information. It was found that the main geological, mining and economic factors must be studied and evaluated separately and ranked according to their importance.

In the mining, there are lot of problems containing uncertainty and vagueness hampering the proper solution of many problems. Minch et al. [60,61] discussed utilization of simple fuzzy expert diagnostic system for evaluation of diamond core drilling by means of impregnated diamond bits. For this purpose the knowledge base consisting of precise data of monitoring of drilling and expert experiences of drilling was created. Although this technique with using the expert system cannot be considered as universal, the knowledge base for the given expert system is the tool enabling to overcome many problems with uncertainty and vagueness and so future application of similar systems in the field of mining research and industry will be definitely successful. Deb et al. [62] outlined the analysis of vagueness and uncertainty in data using fuzzy reasoning techniques and establishes relations between input and output based on fuzzy rules designed using field data. The author has chosen three parameters, coal mine roof rate (CMRR), primary roof support (PRSUP) and intersection diagonal span (IDS) are found that it is directly related to roof fall rate (RFR). It is said that one way of simplifying a complex system is to permit some degree of uncertainty in its description as stated by Klir et al. [63]. In mining industries no mines are identical and each mine has its own unique set of mining conditions geological setup. In order to study the condition of various mines for efficiency, safety and economy reasons, a fuzzy model was presented by Li et al.[64] based on fuzzy evaluation. Relevant data from five mines were collected and the model was used to evaluate the mining condition of these mines. The evaluation results are in conformity with the real situation. The application of fuzzy logic technique in the rock mass classification is direct and generates a fuzzy number representing the classification value. Fuzzy mathematics even introduces the uncertainty in the evaluating of parameters in the rock mass classification. A example may be taken, the index Q rock mass classification. This classification was established in 1974 and is based on six parameters [65]

$$Q = \left(\frac{RQD}{J_n}\right)\left(\frac{J_r}{J_a}\right)\left(\frac{J_w}{SRF}\right) \tag{2.11}$$

Where RQD – Rock Quality Designation

J_n – Joint set number

J_a – Joint alteration number

J_w – Joint water reduction number

J_r - joint roughness number

SRF – Stress reduction factor

By applying fuzzy logic to the equation for the index Q results in the fuzzy classification value with non-linear distribution is obtained.

2.7 Neuro –Fuzzy & Fuzzy–Neuro Hybrid Controller

A hybrid model having a combination of artificial neural network, fuzzy system, and /or genetic algorithms produce better results. For intelligent system to be robust various combinations is quite necessary. The neuro- fuzzy hybrid model , which involves the integration of ANN & FL techniques are perhaps the most popular hybrid technique used in engineering problems. The ANN technique is normally used as the learning algorithm for the defuzzification process in FL based models. The Neuro –fuzzy hybrid models are regarded as black box model which provides little insight to help understand the underlying process [66]. Neuro fuzzy model are able to take advantage of the fuzzy inference mechanism capabilities in fuzzy logic as well as the learning ability of neural networks. In adoptive neuro-fuzzy inference system (ANFIS) model both of the learning capabilities of neural network and reasoning capabilities of fuzzy logic were combined in order to give enhanced prediction capabilities as compared to using single methodology alone. The goal of ANFIS is to find an appropriate model or mapping that will correctly associate the input values with the target values. The FIS is a representation of knowledge where each fuzzy rule describes a local behavior of the system. The network structure that incorporates FIS and employs hybrid learning rule to train is called ANFIS [1]. In this hybrid intelligent system researchers have predicted unconfined compressive strength (UCS) and tangent young's modulus (E) of rock having better performance. According to Singh et al. [39] neuro- fuzzy method has a good potential to model complex, non-linear and multivariate engineering problems. They have compared the results of physic – mechanical properties of rock and found that Neuro-fuzzy method is better than the ANN method alone though the results obtained from ANN were also satisfactory. Fuzzy logic technique can be used in conjunction with ANNs in more than one way to provide solutions for control problems, decision making, and pattern recognition. The most common and easiest way of integrating the two technologies is the fuzzy logic implementation by ANNs leading to neuro-fuzzy systems. Fuzzy Logic systems provide means of capturing uncertainty. Uncertainty is inherent in almost every real-world problem. The essential characteristics of fuzzy logic technique are as follows by Zadeh et al. [67]:

- Exact reasoning is viewed as a limiting case.
- Everything is a matter of degree.
- Inference is viewed as the process of propagation of elastic constraints.
- Any logical system can be fuzzified.

The integration of ANNs with fuzzy systems results to a Fuzzy Neural Network (FNN) of one of the following types as suggested by Schalkoff et al. [68]:

- FNN with crisp number of inputs and fuzzy weights.
- FNN with fuzzy set input signals and crisp weights.
- FNN with both fuzzy input signals and fuzzy weights.

A possible FNN structure consists of a layered net with an input layer implementing membership functions, a first hidden layer implementing fuzzy rules and combining membership functions, a second hidden layer combining fuzzy values, and an output layer providing defuzzification. Figure 2.12 illustrates an approach to FNN implementation.

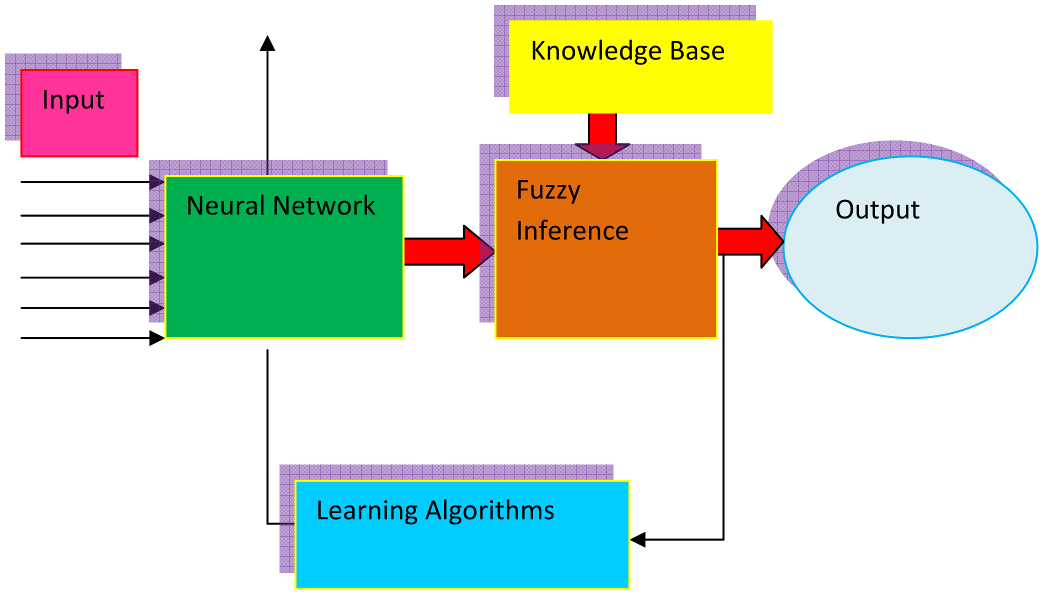


Figure 2.12 FNN implementation

The benefits of the neural network technology is the generalization ability about the untrained samples due to the massively parallel interconnections and the ease of implementation simply by training with samples for any complicated rule or mapping problem. The utility of fuzzy sets lies in their ability to model the uncertain or ambiguous or vague data so often encountered in real life. Therefore, to enable a system to take care of real life problems in a manner more like humans, the concept of fuzzy sets has been incorporated into the neural network by Lin et al. [69]. Sinha et al. [70] described in general that there are two types of combinations between neural networks and fuzzy systems. In the first combination neural network and fuzzy system work independently of each other. The combination lies in the determination of certain parameters of a fuzzy system by a neural network technique, or a neural network-learning algorithm. This can be done offline, or online while using the fuzzy system. The second kind of combination defines a homogenous architecture, usually similar to the architecture of a neural network. This can be done by interpreting a fuzzy system as a special kind of neural network, or by implementing a fuzzy system with the help of neural network. Apart from these models, there are approaches in which a neural network is used as a pre-processor or as a post-processor to a fuzzy system. Such combinations do not optimize a fuzzy system, but only target to improve the performance of the combined system. Learning takes place in the neural network only; the fuzzy system remains unchanged .

Rangel et al. [71] presented an alternative strategy to evaluate the stability problems of tunnels during the design and construction stages based on a hybrid system , composed by neural, neuro-fuzzy and analytical solutions. A prototype of this system is designed & developed using a database formed by 261 cases, 45 real and the rest synthetic. This system is capable of reproducing the displacements occurred at the periphery of the tunnel before and after support installation. The stability of the excavation process is evaluated using a criterion that considers dimensionless parameters based on the shear strength of the media, the level of induced deformation in the ground, the plastic radii and the advance of excavation without support. The efficiency and validity of the prototype is checked with two examples of actual tunnels, one included in the database used to train the system and the other not included. The results of both examples show a better approximation than any other commonly used techniques. According to Hoffmann et al. [72] AI computing constituent and its strength has been studied as Artificial Neural Network and Fuzzy Logic are for learning and approximation & approximate reasoning respectively.

Also a comparison has been done between fuzzy system and artificial neural network as depicted in table 2.2 [73].

TABLE 2.2 Comparison between fuzzy system & Artificial Neural Network

Sl. Nos.	**Strength parameters**	**Fuzzy System**	**Neural Network**
1.	Mathematical model	Slightly good	Bad
2.	Learning ability	Bad	Good
3.	Knowledge representation	Good	Bad
4.	Expert knowledge	Good	Bad
5.	Non-linearity	Good	Good
6.	Optimisation ability	Bad	Slightly good
7.	Fault tolerance	God	Good
8.	Uncertainty tolerance	Good	Good
9.	Real time operation	Good	Slightly Good

2.7.1 Neuro -Fuzzy Hybrid Controller Applied in Underground Mines

In artificial intelligence technique neuro-fuzzy refers to combination of artificial neural network and fuzzy logic technique. Fuzzy system has the ability to make use of knowledge expressed in the form of liguistic rule,thus they offer the possibility of implementing expert human knowledge and experience.Usually, tuning of various parameters of membership function is time consuming task. Artificial neural network technique can automate this significantly reducing development time and resulting in better performance. Neuro fuzzy hybridization results in hybrid intelligent system that synergize these two techniques by combining human like reasoning style of fuzzy system with the learning of connectionist strucure of neural netwrk. In undergrund mines this hybridization of neuro-fuzzy technique was tried successfully in mine subsidence,ores estimation, rock mass characterisation, mine ventilation rock mass blasting etc. Venkatesh et al.[74] have used this superior technique for estimation of shear strength parameters of cohesive soil and the results revealed that neuro fuzzy model can be effective , versatile and useful way to measure the shear strength parameter of soil. Researchers have stated that the greater number of input parameters resulted redundancy in rule base causing decrease in efficiency of prediction models. Limiting the input vectors 2 or 3 could have given better regression values. In this hybrid technique output of neural network are fed into the fuzzy inference system in the form of membership functions to get the more accurate and appropriate desired output.

2.7.2 Fuzzy-Neuro Hybrid Controller Applied in Underground Mines

The theory of fuzzy logic developed by Zadeh [51] can be very well used to model imprecision , ambiguity and fuzziness in vague linguistic informations . Deli et al. [75] developed a fuzzy neural network learning model by integrating an unsupervised fuzzy neural network classification algorithm with genetic algorithm an AI technique and an adaptive conjugate gradient neural network learning algorithm, and applied to the domain of image recognition. Fuzzy neural network model based control is one of the best suggested intelligent controls. It has the salient feature of constructing a robust control system for factors such as nonlinearity, friction properties, variation in load and system parameters, and unknown disturbances in servo system. In this technique output data from fuzzy inference system are fed into artificial neural network technique as input data thus getting a targeted output by using appropriate backpropagation technique. This particular controller can be used successfully in various imprecise and unpredictable activities like in underground mining operations e.g. blasting, subsidence, ventilation, rock characterization, support etc.

2.8 Rule Based Hybrid Controller

If – then rules are common forms of knowledge representation widely used in expert systems. Systems adopting such rules as the major representation paradigm are called rule – based systems. The first popular computational uses of rule – based systems were the work by Newell et al. [76]. In their work the rules were used to model human behavior problem solving. However, the mathematical model of production systems was used earlier by Post [77] in the domain of symbolic logic. Work on rule – based systems has been motivated for two different objectives. One of these is psychological modeling [35]. The aim of this modeling is to create programs that embody a theory of human performance habits of simple tasks and reproduce human behavior. There are number of theories, which on the basis of rules try to explain human behavior. The most common are SOAR Rosenbloom et al. [78] and ACT Anderson [79]. The other objective aims at creating expert systems, which exhibit intelligent problem solving behavior in some domain.

According to Jantzen [80] the rules may use several linguistic variables both in the condition and the conclusion of the rules. The controllers can therefore be applied to both multi-input-multi-output (MIMO) problems and single-input-single-output (SISO) problems. The typical SISO problem is to regulate a control signal based on an error signal. In fact, the controller may need both the error, the change in error, and the accumulated error *as* inputs, but we will call it single-loop control, because in principle all three are formed from the error measurement. To simplify, this section assumes that the control objective is to regulate some process output around a predetermined set point or reference. The presentation is thus limited to single-loop control because in principle all three are formed from the error measurement .Basically, a linguistic controller contains rules in the if-then format, but they can be presented in different formats too. In many systems, the rules are presented to the end-user in a format similar as shown below,

1. If error is Neg and change in error is Neg then output is NB

2. If error is Neg and change in error is Zero then output is NM

3. If error is Neg and change in error is Pos then output is Zero

4. If error is Zero and change in error is Neg then output is NM

5. If error is Zero and change in error is Zero then output is Zero (2)

6. If error is Zero and change in error is Pos then output is PM

7. If error is Pos and change in error is Neg then output is Zero

8. If error is Pos and change in error is Zero then output is PM

9. If error is Pos and change in error is Pos then output is PB

The names Zero, Pos, Neg are labels of fuzzy sets as well as NB, NM, PB and PM (Negative big, negative medium, positive big and positive medium respectively).

2.8.1 Rule Based Hybrid Controller Applied in Underground Mines

Some researchers [81-83] have suggested feed-forward sensory driven approach termed rule based control (RBC). In the RBC, a stimulation signal for the muscles is determined on the basis of the sensory data by applying a set of predefined control rules. The RBC approach, being robust and predictive, is a powerful solution for the control of Functional Electrical Stimulation (FES). This new and robust technique could successfully be used in underground mines for any complex problem. It is a real time control system. In the rule base system the knowledge of the environment is stated in the form of different rules. Knowledge representation formalism used in expert system is primarily based on rules. The main components of the typical rule base system are: the working experience memory, the rule base and the inference engine. The working memory contains information about the particular event of the problem being solved. A rule contains a set of conditions (antecedents) and a set of conclusions (consequents). The inference engine uses the rule base and the working memory to extract the new information. The rule base controller is basically a look table technique for representing complex nonlinear system. All rule based system need a control technique to decide conflicts between two or more applicable rules. Mostly, the environmental conditions affect the entire rule base. Possibility of modifying all the rules at once using Clementine rule base software [84] rather than modifying each rule individually is investigated.

Comparison of AI technique feature is depicted in table 2.3[66]

Table 2.3 Comparison of AI techniques features

Sl.Nos.	Methods	Learning capacity	Knowledge representation capacity	Real time operation functionality	Optimisation capacity	Data requirement	Expert input level
1.	Artificial Neural Network	VH	H	H	M	VH	VL
2.	Fuzzy Logic	M	VH	M	VH	M	VH
3.	Fuzzy Neuro	M	H	M	L	M	VL

VL – Very Low

L - Low

M – Medium

H – High

VH – Very High

2.9 Summary

Certainty is inherent in almost every real-world problem. Underground mining is an imprecise and unpredictable activity. In this chapter literature review of various AI techniques like Artificial Neural Network, Fuzzy Logic and its hybridization applying to mine support in underground mines have been given. Limited work has been done for mining with hybridization techniques. In the next chapter different excavation parameters have been analysed.

CHAPTER 3

ANALYSIS OF DIFFERENT PARAMETERS DURING EXCAVATION

3 Analysis of Different Parameters during Excavation

This chapter 3 describes the different parameters associated with the mine excavation. Till date these parameters are inter related by empirical relations. In fact, the mining industry relies heavily upon empirical analysis for design and prediction (40). Some of the potential parameters affecting directly to the support characteristic are explained below.

3.1 Introduction

As safety is the prime responsibility of an engineer in underground mines the potential for Artificial intelligence techniques to assist in predicting setting load on prop should be investigated. Various input parameters of mines give key information in required parameters prediction. Though there are a lot of parameters are responsible for successful mine excavation. Each parameter has its own effect on the mining activity. Some of the most influential parameters which affect underground mining activities are discussed here.

3.2 Field Analysis of Different Parameters

3.2.1 Datasets

Different data sets as input parameters discussed in chapter 2. Out of these some of the input informations collected from 4 underground mine are listed below and Table 3.1 provides the representative data or data table used as input.

Rock Mass Rating: RMR was initially developed [65] in 1973 bases rock mass quality on five parameter basis:

- uniaxial compressive strength of the rock
- rock quality designation (RQD)
- spacing of discontinuities
- condition of discontinuity
- ground water conditions.

These factors are given a numerical value and totaled together to get an RMR value. This value will be a number between 0 and 100 with zero being very poor rock and 100 being extremely good rock. The ground water conditions were assumed to be dry conditions. RMR varies from mine to mine.

Distance of prop from the face: Installation of the props from the face done as per fix pattern .Setting load requirement for each prop may be different. The distances may be from 0.4m to 0.8m.

Working height: Working height varies from mine to mine as per their geological characteristic and coal seam thickness. It was taken from 2.4 m to 4.5m in the present study.

Rock density: Rock density has much influence on mineability of an underground mine. It is dependent on the rock properties. The value taken here is from 2.2 t per cubic meter to 3.0 t per cubic meter.

Seam thickness: Seam thickness depends upon the amount of coal reserve of a particular area. Method of mining is also decided as per seam thickness. In this study it is taken from 3.4 m to 4.8 m.

Width of gallery: Rock load is calculated on the basis of overhanging roof and number of support to be erected are also decided on rock load. Hence width of gallery has major impact on support load given. Here it is taken from 4.0 m to 4.5 m.

Charge per hole: Amount of Charge per hole is responsible for dislodging of erected support. Thus initial setting load depends upon amount of charge given in a hole. Its range is 400g to 600g.

Setting load on prop: Setting load applied to the respective prop is to be taken care as it may be responsible for mine accident. Presently it is chosen arbitrarily or as per regulatory authority's guidelines based on no critical study. It is taken in the range of 6 ton to 10 ton per prop.

Table 3.1 Data sets of input parameters

Sl.Nos.	Parameters	Set1	Set2	Set3	Set4	Set5	Set6	Set7	Set8	Set9	Set10
1.	RMR	42	55	43	56	42	57	49	38	58	47
2.	Distance of first prop from the face (d1) (m)	0.6	0.8	0.4	0.6	0.4	0.6	0.8	0.8	0.6	0.6
3.	Distance of second prop from the face (d2)(m)	1.2	1.4	1.0	1.0	0.8	1.2	1.2	1.2	1.2	1.4
4.	Distance of third prop from the face (d3) (m)	1.8	2.0	1.6	1.4	1.2	1.8	1.6	1.6	1.8	2.2
5.	Distance of fourth prop from the face (d4) (m)	2.4	2.6	2.2	1.8	1.6	2.4	2.0	2.0	2.4	3.0
6.	Distance of fifth prop from the face (d5) (m)	3.0	3.2	2.8	2.2	2.0	3.0	2.4	2.4	3.0	3.8
7.	Distance of sixth prop from the face (d6) (m)	3.6	3.8	3.4	2.6	2.4	3.6	2.8	2.8	3.6	4.6
8.	Working Height (m)	2.7	2.6	3.0	2.4	2.6	4.5	3.0	4.5	3.0	3.0
9.	Rock Density(gm/cc)	2.2	3.0	2.4	2.8	2.6	2.2	2.4	3.0	2.3	2.8
10.	Seam Thickness (m)	3.4	4.1	4.8	3.4	3.8	4.8	4.4	6.4	3.6	3.6
11.	Width of Gallery (m)	4.2	4.2	4.5	4.2	4.2	4.2	4.0	4.2	4.2	4.2
12.	Charge per Hole at the coal face(g)	400	400	450	450	400	500	400	400	500	600
13.	**Target** – Setting load on standing prop (1) (Ton)	09	07	10	06	10	07	08	10	06	08

Installations of props are shown in figure 3.1. Six nos. of props were installed in front of coal face on each side of the side wall. In this thesis only prop row in the left side was considered for experimentation. Blasting pattern or blast drill hole orientation in the coal face is decided by the mine authority as per available geological information.

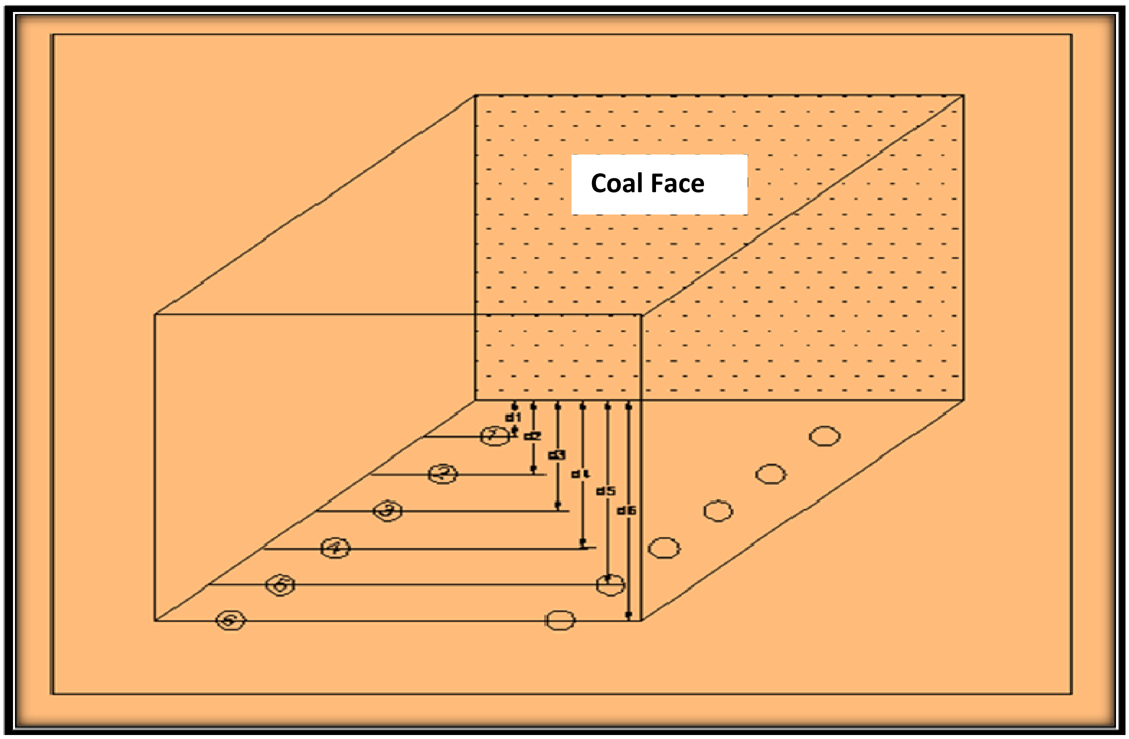


Figure 3.1 Installation of props

Orientation of props and roof bolts in a underground mine are shown in figure 3.2 below. In this picture of a mine props and roof bolts have been shown installed in two separate rows.

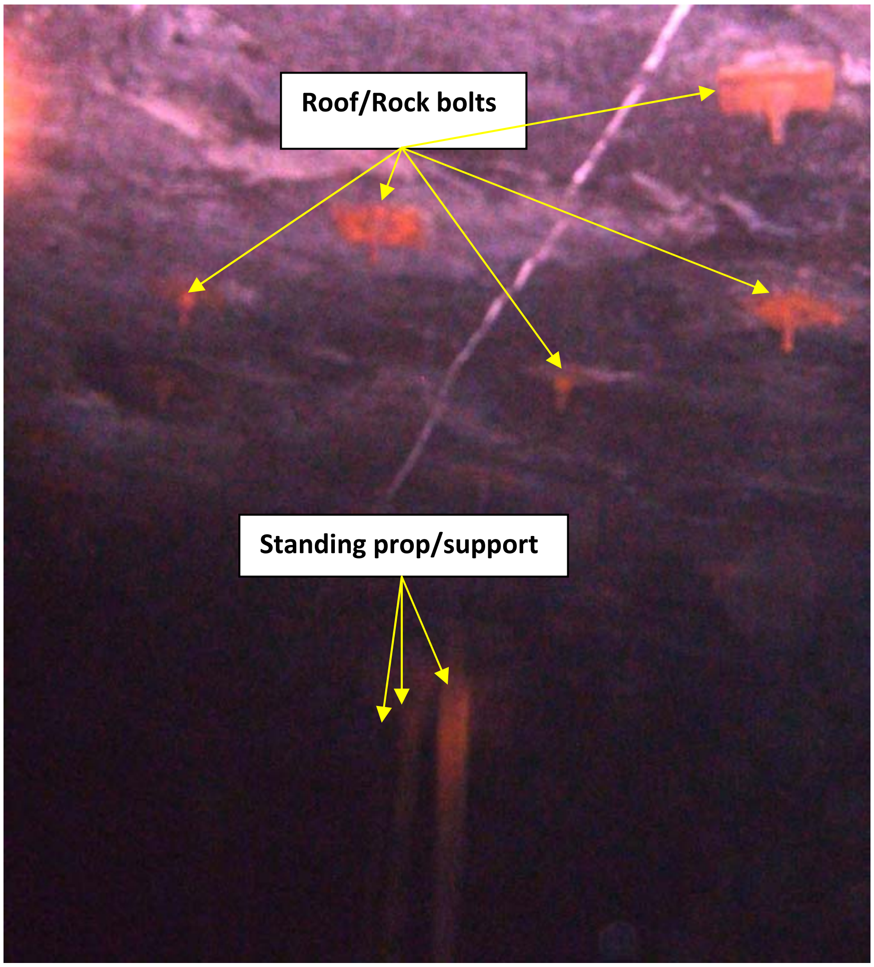


Figure 3.2 Orientation of props and roof bolts in underground mine

3.3 Summary

Input data were collected from mines which are considered to be more effective and influential on setting load on prop. Latter with these data amount of setting load were approximated by neural network, fuzzy logic techniques and rule based technique and their hybridization. Next chapter deals with the analysis of setting load on prop by neural network technique.

CHAPTER 4

OPTIMISATION OF MINE SUPPORT PARAMETERS USING NEURAL NETWORK TECHNIQUE

4. Optimisation of Mine Support Parameters using Neural Network Technique

The use of Artificial Neural Network in mining engineering has become extremely widespread in the last few years. In this chapter, mine support parameters which have great influence on the underground mine support mechanism have been collected from the mines. These data were taken as input data for prediction of load on support equipments like props and rock bolts as output with the help of ANN.

4.1 Introduction

Artificial neural network were used to determine ore boundary delineation, aggregate quality and rock indentation depth [85,86], ore reserve estimation [28] and real time roof pressure in geotechnical researches[87]. In the field of remote sensing, neural network were used for the determination of different lithological regions [88]. Neural network can also serve as a tool which helps to determine the relative importance of the factors influencing the stability of underground objects according to their importance [22]. ANN is also used to determine the event type (earth-quake, quarry and mining blast, chemical explosion etc. [89]. But very few researchers have touched upon the support systems which contribute a major role to upkeep safety in underground mines.

4.2 Analysis of Mine Support Parametric Data using Neural Network Mechanism

The artificial neural network which was used here is six- layers perceptrons. This number of layers has been found to ease the training of the network. The activation function used here is Sigmoidal .The input layer has twelve neurons representing each neuron one parameter. The different twelve parameters are for this study are Rock Mass Rating (RMR), distance of first prop from the face, distance of second prop from the face, distance of third prop from the face, distance of fourth prop from the face, distance of fifth prop from the face, distance of sixth prop from the face, working height, rock density, seam thickness, width of gallery and charge per hole. The output layer has single neuron which produces the setting load. The first hidden layer, second hidden layer, third hidden layer and fourth hidden layer has 30, 14, 7 and 4 neurons respectively. These numbers of hidden layers were also found empirically. Figure 4.1 depicts the neural network architecture with its input and output signals.

The neural network was first trained to estimate the setting load to be applied in respective prop.

In figure 4.1 the input parameters are

RMR: Rock mass rating

DF1: Distance of 1st prop from the face

DF2: Distance of 2nd prop from the face

DF3: Distance of 3rd prop from the face

DF4: Distance of 4th prop from the face

DF5: Distance of 5th prop from the face

DF6: Distance of 6th prop from the face

WOH: Working height

ROD: Rock density

SEM: Seam thickness

WIG: Width of gallery

CHH: Charge per hole

The different data which has been taken from mine site for training of the network is much larger. To train the network 60 sets of such data were taken which is depicted in table 4.1.

Table 4.1 Examples of training patterns

RMR	DF1	DF2	DF3	DF4	DF5	DF6	WHO	ROD	SEM	WIG	CHH	SLP
38	0.4	1.0	2.1	1.6	2.4	2.6	2.8	2.3	3.6	4.0	400	8
40	0.5	0.9	1.2	1.7	2.5	2.4	2.7	2.2	3.4	4.1	490	7
39	0.6	0.7	2.0	1.8	2.2	2.5	2.6	2.3	4.8	4.2	580	6
38	0.4	0.8	1.9	1.9	2.3	3.5	2.7	2.2	3.9	4.5	455	5
40	0.5	0.9	1.2	2.9	2.4	2.8	2.9	2.5	3.7	4.1	450	9
39	0.7	1.2	2.0	2.2	3.1	3.2	2.5	2.4	4.5	4.3	430	7

40	0.5	1.1	1.8	2.5	3.1	2.9	2.6	2.5	3.6	4.1	460	9
42	0.7	1.3	1.9	2.3	3.2	2.6	3.8	2.6	3.7	4.2	500	8
39	0.6	0.9	1.6	1.7	2.1	2.5	2.6	2.3	3.6	4.3	400	6
45	0.4	1.0	1.5	2.4	2.4	3.0	2.5	2.7	3.4	4.2	450	9
55	0.7	0.8	1.3	1.8	3.6	3.3	2.4	2.9	4.5	4.4	560	5
44	0.4	0.9	2.0	2.8	3.4	4.2	3.5	2.3	3.6	4.2	500	7
46	0.6	1.1	2.1	2.2	2.9	2.5	3.6	2.2	3.7	4.0	488	6
42	0.7	0.8	1.2	2.9	2.3	2.7	2.5	2.6	3.5	4.3	460	5
38	0.5	1.2	1.3	1.9	2.1	2.5	2.7	2.3	3.4	4.1	430	8
53	0.6	0.9	2.1	2.2	2.8	3.1	3.3	2.9	4.2	4.4	459	6
51	0.7	0.8	2.2	1.7	3.6	3.2	2.8	2.3	3.5	4.3	400	5

40	0.5	0.9	1.5	2.5	2.2	4.4	3.8	2.4	4.2	4.1	440	7
39	0.4	1.1	2.1	2.6	3.0	2.5	2.9	4.4	4.2	4.0	450	8
55	0.8	1.2	1.3	2.2	2.1	2.5	3.1	2.8	3.5	4.4	400	5
38	0.5	0.9	1.2	1.7	2.5	2.4	2.7	2.2	3.4	4.1	540	7
39	0.6	0.7	2.0	1.8	2.2	2.5	2.6	2.3	3.8	4.2	460	6
38	0.4	0.8	1.9	1.9	2.3	3.5	2.7	2.2	3.9	4.5	550	5
43	0.5	0.9	1.2	2.9	2.4	2.8	2.9	2.5	3.7	4.1	450	8
45	0.4	1.0	1.5	2.4	2.4	3.0	3.5	2.7	3.4	4.2	470	9
46	0.5	1.1	2.1	2.2	2.9	2.5	3.6	2.2	3.7	4.0	580	6
38	0.4	0.8	1.9	1.9	2.3	3.5	2.7	2.6	3.9	4.5	455	5
40	0.5	0.9	1.2	2.9	2.4	2.8	2.9	2.5	3.7	4.1	450	9

50	0.4	1.1	1.8	2.5	3.1	2.9	2.6	2.9	3.6	4.4	460	7
39	0.7	0.7	2.0	1.8	2.2	2.5	2.8	2.3	3.8	4.2	520	6
38	0.4	1.0	2.1	1.6	2.4	2.6	2.5	2.5	3.6	4.0	400	8
40	0.5	0.9	1.2	1.7	2.5	2.4	2.7	2.2	3.4	4.1	490	7
42	0.7	1.3	1.9	2.3	3.2	2.6	3.8	2.6	3.7	4.2	500	8
39	0.6	0.9	1.6	1.7	2.1	2.3	2.8	2.4	3.6	4.3	400	6
40	0.7	0.7	2.0	1.8	2.2	2.5	2.6	2.3	3.8	4.2	520	6
38	0.4	1.0	2.1	1.6	2.4	2.6	2.8	2.8	3.6	4.0	400	8
40	0.5	0.9	1.2	1.7	2.5	2.4	2.7	2.2	3.4	4.1	490	7
42	0.7	1.3	1.9	2.3	3.2	2.6	3.8	2.6	3.7	4.2	500	8
39	0.6	0.9	1.6	1.7	2.1	2.5	2.6	2.3	3.6	4.3	400	6

53	0.6	0.9	2.1	2.2	2.8	3.1	3.3	2.9	4.2	4.4	459	6
51	0.7	0.8	2.2	1.7	3.6	3.2	2.8	2.3	3.5	4.3	400	5
55	0.6	0.9	2.1	2.2	2.8	3.1	3.3	2.9	4.2	4.4	459	6
42	0.5	1.2	1.5	2.5	2.2	4.4	3.8	2.4	4.7	4.1	540	7
51	0.7	0.8	2.2	1.7	3.5	3.2	2.8	2.3	3.5	4.3	400	5
40	0.6	1.1	1.8	2.5	3.1	2.9	2.6	2.2	3.6	4.1	460	9
39	0.7	0.7	2.0	1.8	2.2	2.5	2.6	2.3	3.8	4.2	520	6
55	0.8	1.2	1.3	2.2	2.1	2.5	3.1	2.8	3.5	4.4	400	5
38	0.5	0.9	1.2	1.7	2.5	2.4	2.7	2.2	3.4	4.1	570	7
42	0.7	0.8	1.5	2.8	2.3	2.7	4.2	2.6	3.5	4.3	460	5
45	0.5	1.2	1.3	1.9	2.1	2.5	2.7	2.3	3.4	4.1	430	8

57	0.6	0.9	2.1	2.2	2.8	3.1	3.3	2.9	4.2	4.4	459	6
51	0.7	0.8	2.2	1.7	3.5	3.2	2.8	2.3	3.5	4.3	400	5
40	0.5	1.1	1.8	2.5	3.1	2.9	2.6	2.9	3.6	4.1	460	9
46	0.4	0.9	1.2	1.7	2.5	2.4	2.7	2.2	3.4	4.4	490	7
39	0.6	0.7	2.0	2.5	2.2	2.5	2.6	2.3	4.8	4.2	580	6
38	0.4	0.8	1.9	1.9	2.3	3.5	2.7	2.2	3.9	4.5	455	5
40	0.5	0.9	1.2	2.9	2.4	2.8	2.9	2.5	3.7	4.1	450	9
50	0.7	1.1	1.8	2.5	3.1	2.9	2.6	2.9	3.6	4.4	460	7
39	0.5	1.2	2.0	2.2	3.2	3.2	2.5	2.4	4.5	4.3	520	7

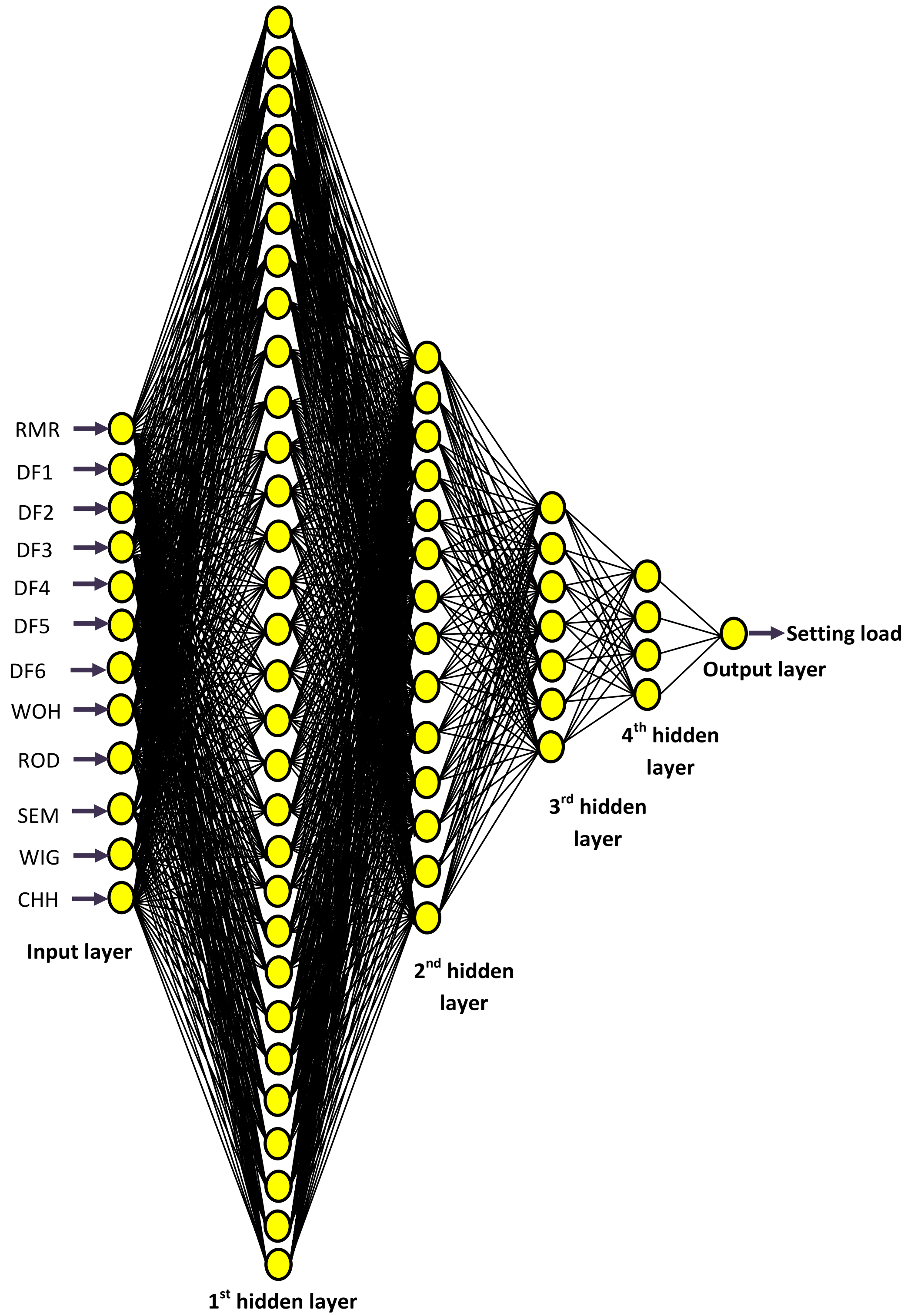


Figure 4.1 Neural network controller

4.3 Simulation Results & Discussion

Neural network is trained for estimation of setting load to be applied on the first prop from the face. The amount of setting load to be given can be predicted on other props also. Table 4.2 shows the setting load applied in actual and estimated in first prop.

TABLE 4.2 Comparison of setting load simulated with neural network and real data

Serial Nos.	Parameters	At mine site(tons)	By neural network technique(tons)
1.	Setting load on first prop from face	9	9.7
2.		7	7.1
3.		10	9.1
4.		6	6.0
5.		10	8.9
6.		7	7.0
7.		8	8.4
8.		10	9.3
9.		6	6.0
10.		8	8.0

By simulation it is seen that setting load obtained from ANN technique is having average percentage variation 4.11 with real mine data.

4.4 Summary

In this chapter with the data sets obtained from mine the artificial neural network were trained and the results are found to be satisfactory. Next chapter deals with analysis of Fuzzy logics for setting load on prop.

CHAPTER 5

OPTIMISATION OF MINE SUPPORT PARAMETERS USING FUZZY LOGIC TECHNIQUE

5 Optimisation of Mine Support Parameters using Fuzzy Logic Technique

This chapter deals with simulation of mine data set in respect of various parameters through fuzzy logic technique and getting setting load for mining props.

5.1 Introduction

Human beings have a remarkable capability to perform many varieties of physical and mental work without any explicit measurements or computations. Examples are, driving in city traffic, parking a car, cleaning a house etc. In performing these tasks human perceptions plays an important role. Perceptions are described by propositions drawn from natural languages, in which the boundaries of perceived classes are fuzzy. It is highly needed to capture the expertise of human being and to utilize the knowledge to develop the AI controller for prediction of setting load to be applied in each prop. Fuzzy logic presents formal methodology for representing and implementing the human expert's heuristic knowledge and perception- based action. Using the fuzzy logic frame work , the attributes of human reasoning and decision making can be formulated by a set of simple intuitive IF (antecedent) – THEN (consequent) rules coupled with easily understandable and natural linguistic representations.

The differences between fuzzy control and conventional control can be summarised as follows:

- A conventional present controller tries to control the behaviour of the process using mathematically derived algorithms, while a FLC employs qualitative linguistic terms that take into account the imprecise and vague nature of real-world processes and systems. Figure 5.1 describes the imprecise and vagueness nature of real world and also representation of fuzzy system

- Unlike conventional controllers, fuzzy logic controllers allow the handling of processes that are either modeled inadequately or not representable mathematically.

- A Fuzzy Logic Controller describes process behaviours based on available empirical or experiential information from sensor systems and/or human operators. FLCs can cope with complex non-linear, multi-variable and time-varying processes without requiring them to be defined in precise mathematical terms. Because of these advantages over conventional control, fuzzy logic control offers an attractive alternative in many practical engineering applications.

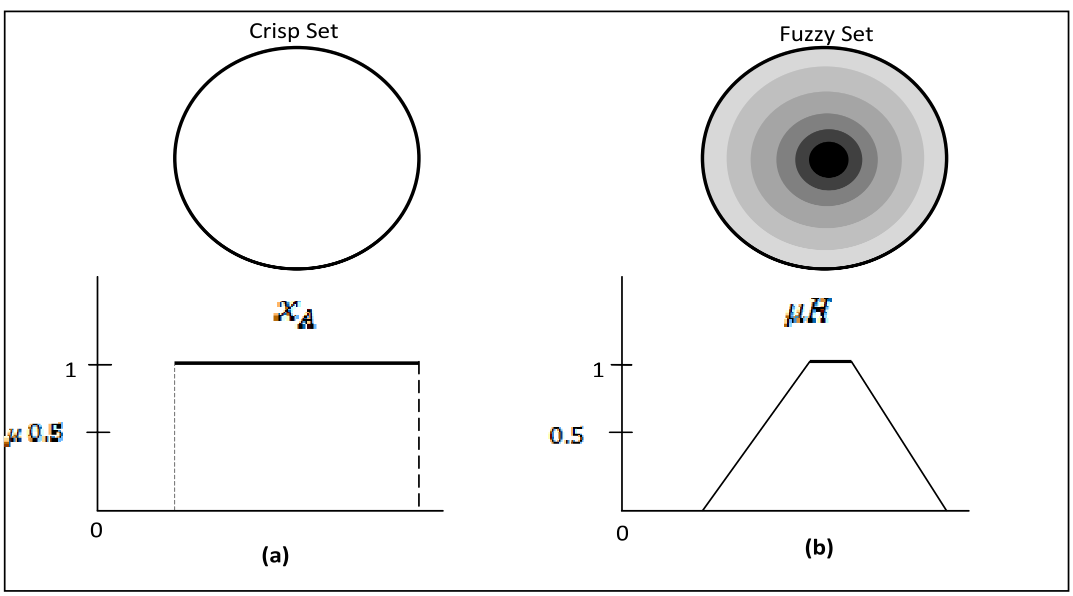


Figure 5.1 Representation of fuzzy system

The logic to infer a crisp outcome from fuzzy input values is Fuzzy Logic [52,90]. The membership function is selected here is triangular. The membership states all information contained in a fuzzy set. Membership functions of fuzzy sets must be precisely defined in respect of function type and function parameters. Both the parameters and shape of the membership functions strongly influence the accuracy [91].

5.2 Analysis of Mine Support Data Using Fuzzy Logic Mechanism

Analysis of Mine Support Data and estimation of setting load Using Fuzzy Logic Controller is depicted below in figure 5.2. In this research triangular membership function is considered. For each 12 parameter i.e. Rock Mass Rating, distance of 6 nos. of prop from the blasting face of the Bord & Pillar mining method, working height of the mine gallery, rock density, seam thickness, width of gallery and charge per hole 5 nos. of linguistic variables are taken. The total nos. of rule formation is 5x5x5x5x5x5x5x5x5x5x5x5 = 244140625= 5^{12}. $(Membership\ function)^{(Nos.\ of\ input\ parameters)}$ .With this 12 nos. of input parameters setting load on the first prop is estimated.

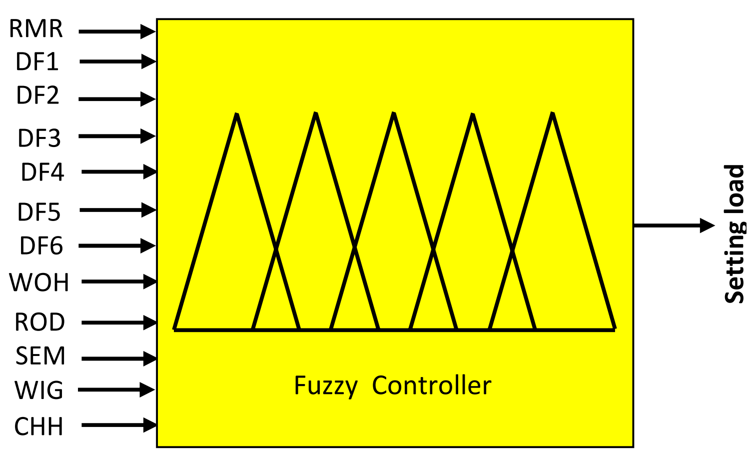


Figure 5.2 Fuzzy logic controller for estimation of setting load

The figure 5.3(a-m) explains the fuzzy membership functions for each parameters

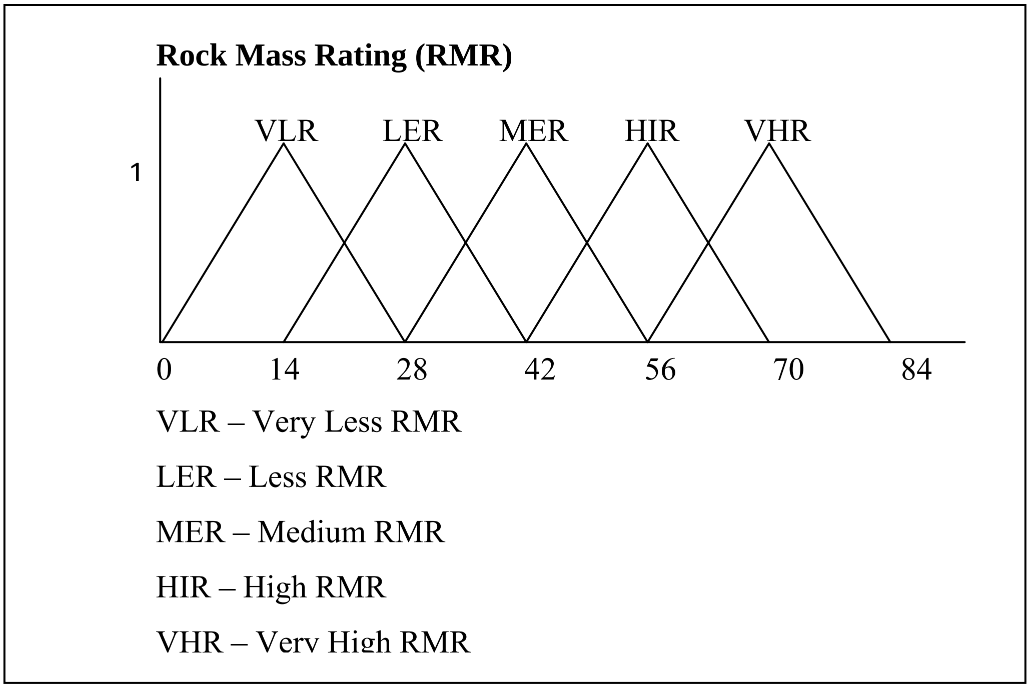


Figure 5.3(a) Fuzzy membership function for RMR

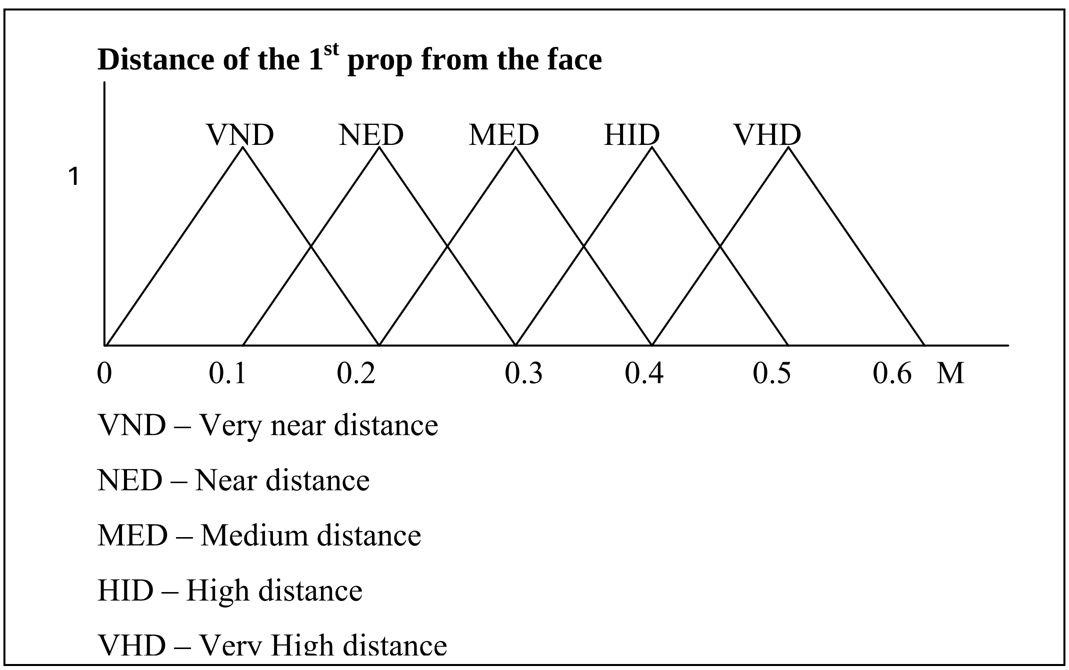
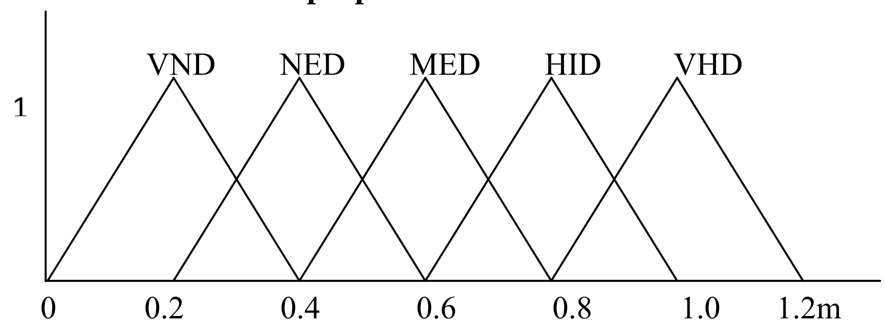


Figure 5.3(b) Fuzzy membership function for distance of 1st prop from the face

Distance of the 2^{nd} prop from the face



VND – Very near distance

NED – Near distance

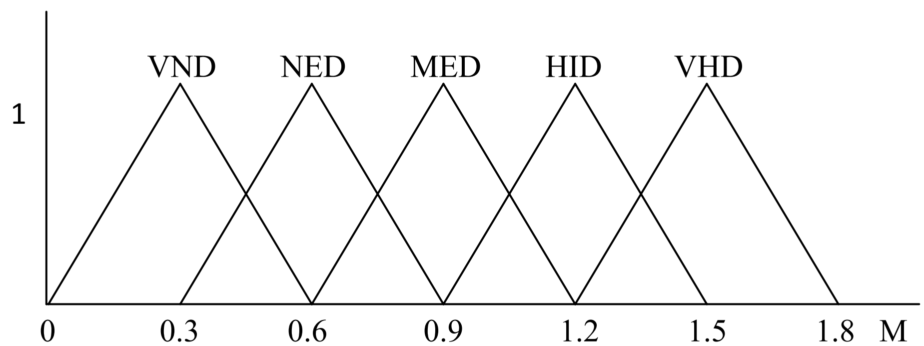
MED – Medium distance

HID – High distance

VHD – Very High distance

Figure 5.3(c) Fuzzy membership function for distance of 2^{nd} prop from the face

Distance of the 3^{rd} prop from the face



VND – Very near distance

NED – Near distance

MED – Medium distance

HID – High distance

VHD – Very High distance

Figure 5.3(d) Fuzzy membership function for distance of 3^{rd} prop from the face

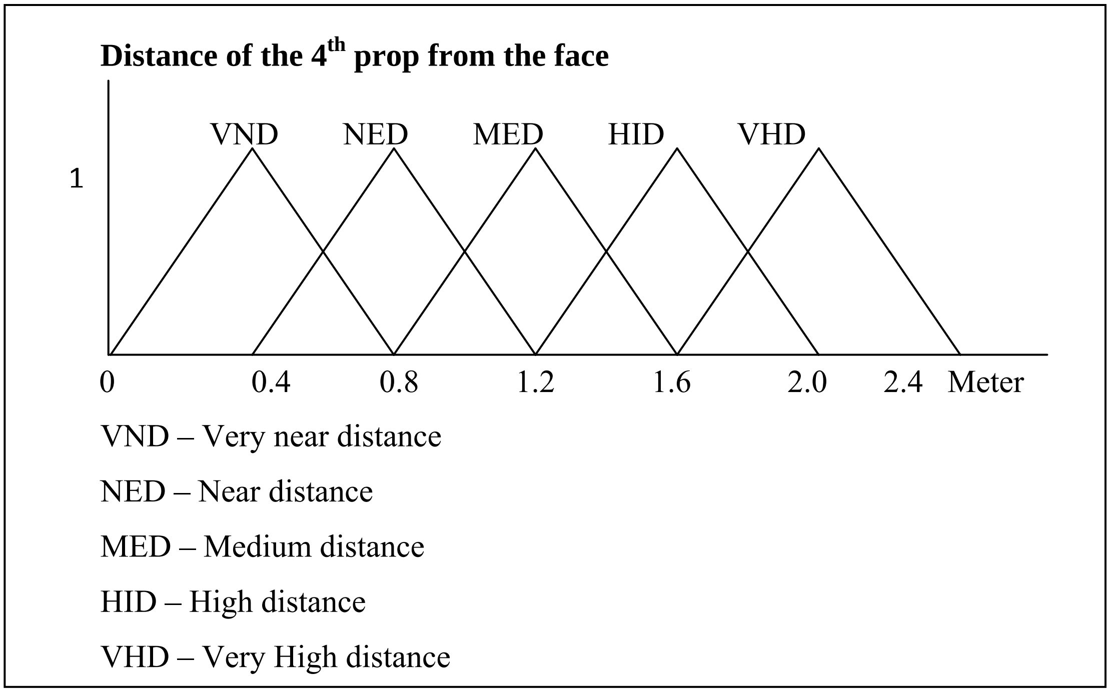


Figure 5.3(e) Fuzzy membership function for distance of 4th prop from the face

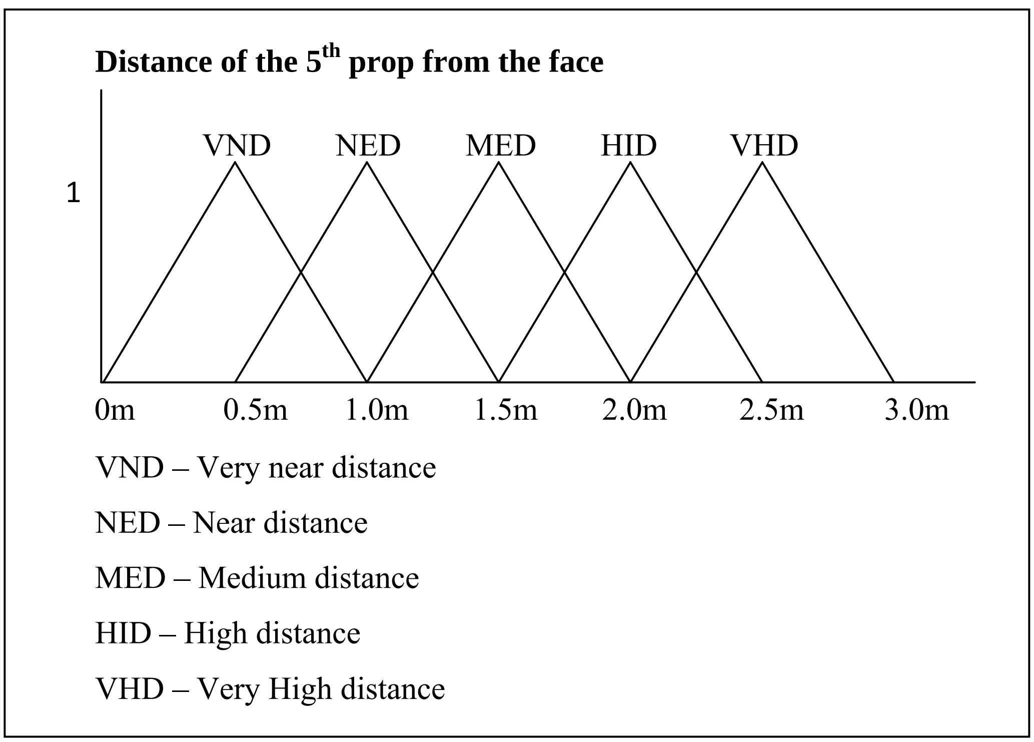


Figure 5.3(f)Fuzzy membership function for distance of 5th prop from the face

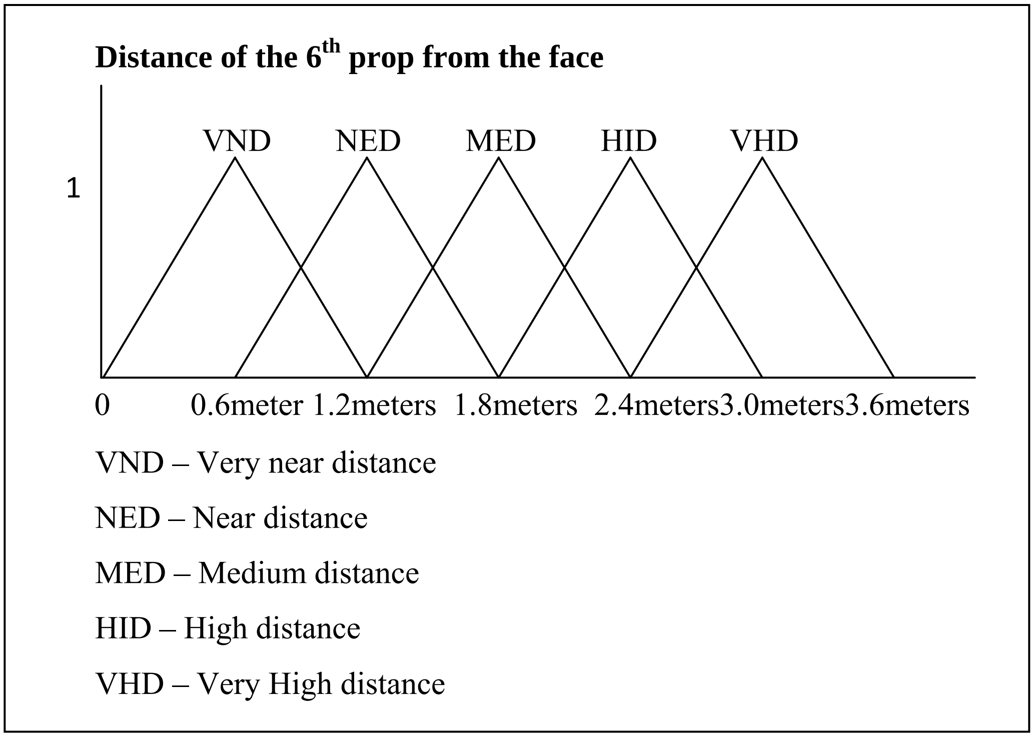


Figure 5.3(g) Fuzzy membership function for distance of 6th prop from the face

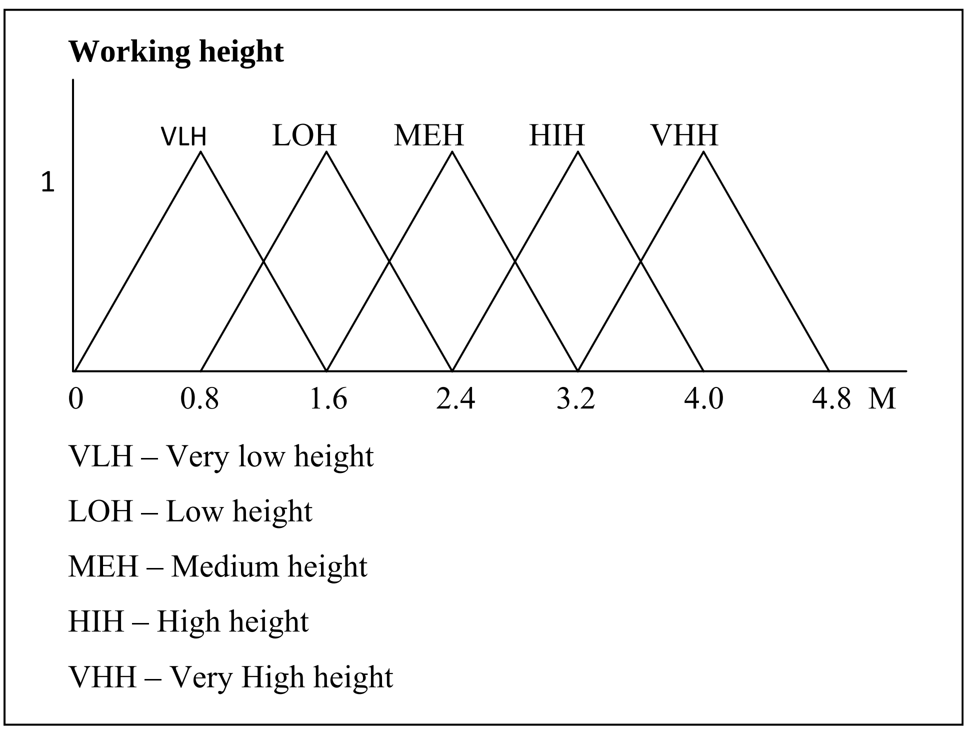
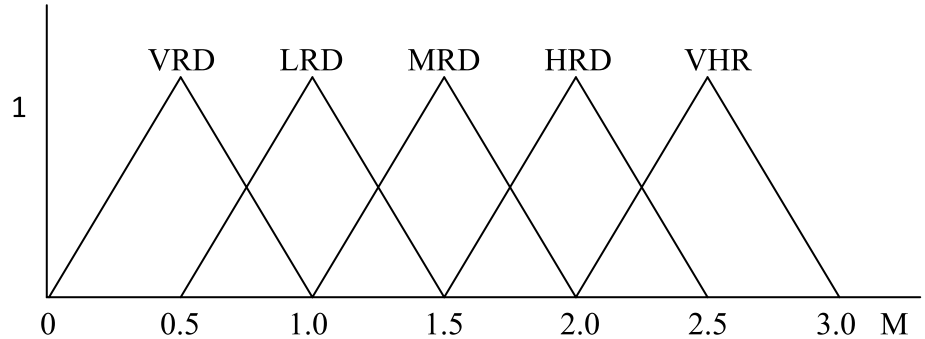


Figure 5.3(h) Fuzzy membership function for working height

Rock density



VRD – Very low rock density

LRD – Low rock density

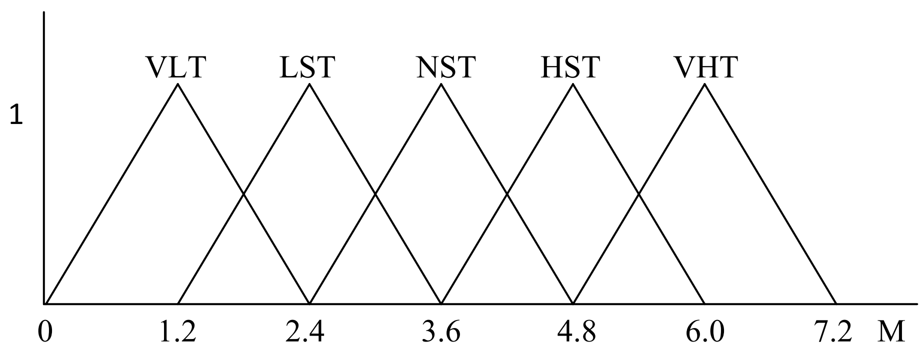
MRD – Medium rock density

HRD – High rock density

VHR – Very High rock density

Figure 5.3(i) Fuzzy membership function for rock density

Seam Thickness



VLT – Very low seam thickness

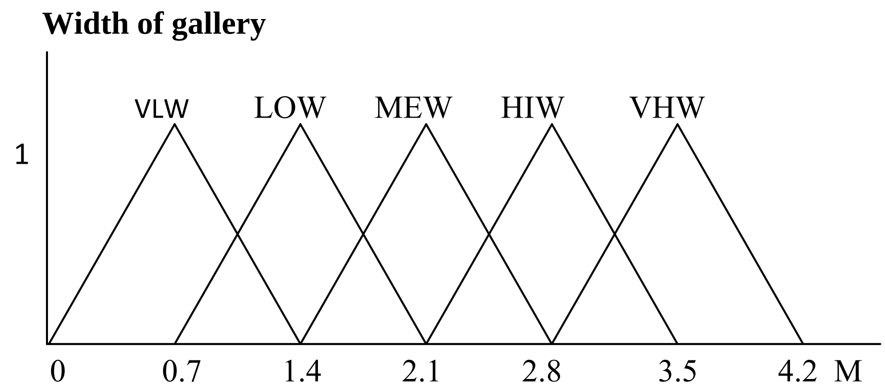
LST – Low seam thickness

MST – Medium seam thickness

HST – High seam thickness

VHT – Very high seam thickness

Figure 5.3(j) Fuzzy membership function for seam thickness



VLW – Very low width of gallery

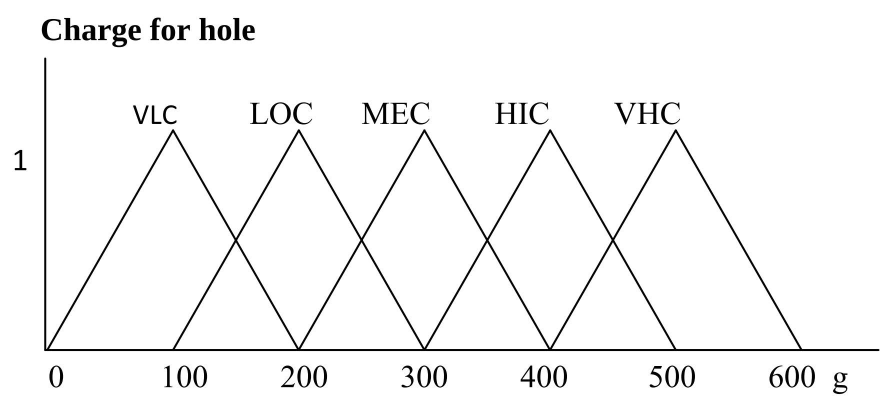
LOW – Low width of gallery

MEW – Medium width of gallery

HIW – High width of gallery

VHW – Very High width of gallery

Figure 5.3(k) Fuzzy membership function for width of gallery



VLC – Very low charge of hole

LOC – Low charge of hole

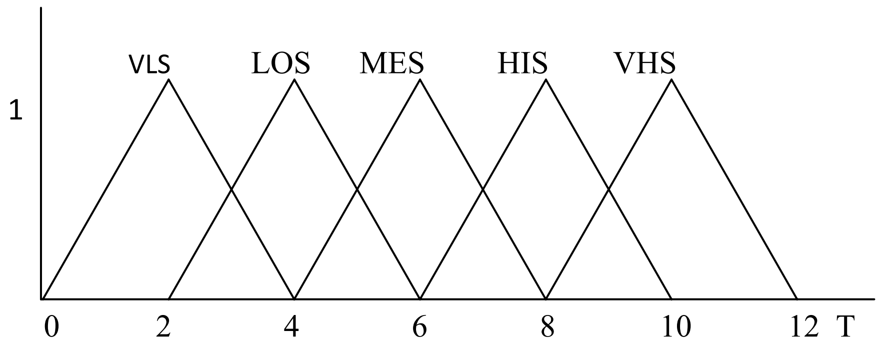
MEC – Medium charge of hole

HIC – High charge of hole

VHC – Very High charge of hole

Figure 5.3(l) Fuzzy membership function for charge per hole

Setting load on prop (Interim)



VLS – Very low setting load on prop

LOS – Low setting load on prop

MES – Medium setting load on prop

HIS – High setting load on prop

VHS – Very High setting load on prop

Figure 5.3(m) Fuzzy membership function for setting load on prop

For the fuzzy logic with 12 inputs and one output and with five membership functions at each input then the total nos. of rules is mentioned above will be 244140625,which is too large . In this large nos. of rules many may not contribute significantly to the problem. Hence good judgement is needed to eliminate unnecessary rules [92]. Some of the rules are depicted below for the above mentioned 12 parameters in table no.5.1. By varying the various input parameters the required setting load on the first prop which is nearer to the blasting face is known. Setting load to be applied on the other prop may be known in similar fashion.

Table 5.1Fuzzy rules

Sl.Nos.	If			INPUT					parameters				Then OUTPUT parameters (Setting load on prop)
	Rock mass rating (RMR)	Distance of 1^{st} prop(DF1)	Distance of 2^{nd} prop(DF2)	Distance of 3^{rd} prop(DF3)	Distance of 4^{th} prop(DF4)	Distance of 5^{th} prop(DF5)	Distance of 6^{th} prop(DF6)	Working height (WOH)	Rock density(ROD)	Seam thickness(SEM)	Width of gallery(WIG)	Charge per hole(CHH)	
1.	MER	VND	MED	NED	VHD	VND	NED	VLH	HRD	VHT	HIW	MEC	VLS
2.	VHR	VND	VND	VND	VHD	HID	NED	VLH	LRD	VHT	HIW	VHC	MES
3.	VHR	VHD	MED	HID	NED	NED	HID	VLH	HRD	VHT	MEW	VHC	LOS
4.	VLR	VND	MED	MED	HID	HID	HID	MEH	MRD	LST	MEW	VHC	MES
5.	LER	MED	VND	VND	MED	MED	MED	MEH	HRD	VHT	VLW	VLC	HIS
6.	VLR	VHD	MED	NED	HID	MED	NED	MEH	VRD	VHT	VHW	VHC	VHS
7.	VLR	VND	VND	VND	VND	VHD	NED	MEH	HRD	VLT	MEW	HIC	HIS
8.	VHR	VND	MED	HID	VHD	NED	MED	VHH	HRD	VHT	LOW	VHC	MES
9.	VLR	VND	VND	VND	VND	VHD	NED	MEH	HRD	LST	MEW	VHC	HIS
10.	MER	VND	VND	VND	VND	VHD	NED	HIH	HRD	LST	MEW	LOC	MES
11.	MER	MED	MED	NED	VHD	VND	NED	VLH	HRD	VHT	HIW	MEC	MES
12.	HIR	VND	VND	HID	VHD	HID	NED	VLH	LRD	VHT	HIW	VHC	HIS
13.	VHR	VHD	MED	HID	NED	NED	HID	MEH	HRD	VHT	MEW	VHC	LOS
14.	VHR	VND	MED	MED	HID	HID	HID	MEH	MRD	LST	MEW	VHC	LOS
15.	VLR	MED	MED	VND	MED	MED	MED	LOH	HRD	VHT	VLW	VLC	MES
16.	VLR	VHD	MED	HID	HID	MED	NED	MEH	VLD	VHT	VHW	VHC	MES
17.	LER	VND	VND	VND	VND	VHD	NED	MEH	HRD	MST	MEW	VHC	VHS
18.	VHR	VND	MED	HID	VHD	NED	MED	VHH	MRD	VHT	MEW	VHC	MES
19.	VLR	VND	VND	VND	VND	VHD	NED	MEH	HRD	LST	VLW	VHC	VLS
20.	MER	VND	VND	VND	VND	VHD	NED	MEH	HRD	LST	MEW	VLC	LOS
21.	VLR	VND	MED	NED	VND	VND	NED	VLH	HRD	VHT	HIW	MEC	HIS
22.	VHR	MED	VND	VND	VHD	HID	NED	MEH	LRD	VHT	HIW	VHC	MES
23.	VHR	VHD	MED	HID	NED	NED	HID	VLH	LRD	VHT	MEW	VHC	HIS
24.	VLR	VND	MED	MED	HID	HID	HID	MEH	MRD	LST	MEW	HIC	VLS
25.	VHR	MED	VND	VND	MED	HID	MED	LOH	HRD	VHT	VLW	VLC	MES
26.	VLR	VHD	MED	NED	HID	NED	NED	MEH	VHR	VHT	MEW	VHC	MES
27.	MER	VND	MED	VND	MED	VHD	NED	VLH	HRD	LST	MEW	VHC	MES
28.	VHR	MED	MED	MED	MED	NED	MED	VHH	HRD	VHT	LOW	LOC	HIS
29.	VLR	VND	VND	VND	VND	VND	VND	MEH	VHR	LST	MEW	VHC	VLS
30.	MER	VND	VND	VND	VND	VND	NED	MEH	HRD	HST	MEW	VHC	MES

5.3 Simulation Results & Discussion

The series simulation tests have been conducted with the different parameters. The fuzzy logic controller is successfully giving the result by choosing any number of input parameters out of the 12 variables. In this chapter, a new intelligent controller has been proposed for prediction of setting load to be applied on the nearest prop to the blasting face using fuzzy logic. It is more efficient than the other traditional reactive behaviour control and also easier to design and implement. In the fuzzy rules linguistic variables were represented. Setting load on the prop no.1 nearest to the blasting face was defuzzified and the estimated load obtained was compared with the practical setting load which was applied at mine site as shown in table 5.2.

TABLE 5.2 Comparison of setting load simulated with fuzzy logic and real data

Serial Nos.	Parameters	Setting load applied on prop at mine site (tons)	Setting load on prop by fuzzy logic technique(tons)
1.	Twelve nos. of input parameters	9	9.5
2.		7	7.0
3.		10	9.0
4.		6	5.8
5.		10	10
6.		7	7.5
7.		8	8.1
8.		10	9.1
9.		6	5.8
10.		8	8.0

By simulation it is seen that setting load obtained from fuzzy logic technique is having average percentage variation 3.96 with real mine data.

5.4 Summary

In this chapter 12 nos. of triangular membership functions were made for 12 nos. of input parameters and one triangular membership function for the target output i.e. setting load on prop. Fuzzy rules were drawn for most contributing decision only and after defuzzification setting load was estimated on prop. The Fuzzy results obtained from the analysis are found to be satisfactory. Next chapter deals with the analysis of Neuro-Fuzzy and Fuzzy-Neuro hybrid techniques, for estimating the prop load.

CHAPTER 6

NEURO-FUZZY & FUZZY-NEURO HYBRID CONTROLLER FOR OPTIMISATION OF MINE SUPPORT PARAMETERS

6 Neuro-Fuzzy & Fuzzy-Neuro Hybrid Controllers for Optimisation of Mine Support Parameters

This chapter describes the optimization of mine support parameters using neuro-fuzzy and fuzzy neuro hybrid techniques. The neural network is a multi-layer perceptron trained with backpropagation and is used for estimation of setting load to be applied in the prop in underground mines. The neuro-fuzzy method comprises a neural network acting as a pre-processor for a fuzzy controller. Similarily, fuzzy –neuro method comprises a fuzzy technique acting as a pre-processor for a neural controller.

6.1Introduction

Each Artificial Intelligence technique has its own strength and weakness. For example, fuzzy system can reason with imprecise information and have good explanatory power. On the other hand, rule for fuzzy inference have to be explicitly built into the system or communicated to it some way; in other way the system can not learn them automatically. Neural network represent knowledge implicitly, are endowed with learning capabilities, and are excellent pattern recognizers. In this metaphor the ANN part stands for the perceptive and signal biological machinery, while the fuzzy part represents the emergent 'higher level 'reasoning aspects. As a result, these two technologies have been integrated in various ways, giving rise to hybrid system that is able to overcome many of the limitations of the individual techniques. Therefore, neuro-fuzzy systems are likely to be wider application in real life problems [93].

Neural networks and fuzzy logic have some common features such as distributed representation of knowledge, model free estimation, ability to handle data with uncertainty and imprecision etc. Fuzzy logic has tolerance for imprecision of data while neural networks have tolerance for noisy data [94] .

6.1.1Advantages of Hybrid Algorithms

The important advantages of the hybrid algorithm is splitting the learning process into independent stages, the adaptation of linear weights and adaptation of parameters of the non-linear membership functions. This algorithm decreases the complexity of the algorithm and at the same time the efficiency of learning increases [39]. Neuro –fuzzy hybrid system combine the advantages of fuzzy systems and neural network .The Artificial Neural Network (ANN) provides a good tool to adjust the expert's knowledge and to automatically generate additional fuzzy rules and membership functions. On the other hand, fuzzy logic enhances the generalization capability of neural network by providing more reliable output when extrapolation is needed beyond the limits of the training data [95].

6.1.2 Need for Neuro-Fuzzy Hybridization

Both neural network and fuzzy systems are dynamic parallel processing systems that estimate input-output functions. They estimate a function without any mathematical model and learn from experience with sample data. Hayashi et al.[96] proved that 1) any rule based fuzzy system may be approximated by neural net and 2) any neural net (feed forward MLP) may be approximated by a rule based fuzzy system.

6.1.3 Different Neuro-Fuzzy Hybridization

Neuro – fuzzy hybridization is done broadly in two ways [97, 98, and 99].

- ✓ A neural network equipped with the capability of handling fuzzy information is known as Fuzzy Neural Network (FNN) and
- ✓ A fuzzy system augmented by neural network to enhance some of its characteristics like flexibility , speed, and adaptability is termed as Neuro-Fuzzy System (NFS)

In a FNN, either the input signals and/or connection weights and/or the outputs are fuzzy subsets or a set of membership value to fuzzy sets. Usually in an ANN, either the input signals and/or connection weights linguistic values such as low, medium high or fuzzy numbers or intervals are used to model these. Neural networks with fuzzy neurons are also termed FNN as they are capable of processing fuzzy information.

A neuro-fuzzy system (NFS), on the other hand is designed to realize the process of fuzzy reasoning where the connection weights of network correspond to the parameters of fuzzy reasoning. Using backpropagation learning algorithms, the NFS can identify the fuzzy rules and learn membership function of the fuzzy reasoning. Normally for an NFS it is to establish one-to-one correspondence between the network and the fuzzy system.

This ANN-Fuzzy and Fuzzy-ANN system hybrid algorithms were used successfully in many engineering problems. Many researchers have applied it to the know the haracterization of rock and its related problems. In this research this technique was used to know the setting load to be given in the prop near the blasting face in bord and pillar mining.

6.2 Analysis of Neuro-Fuzzy Hybrid Controller

The neuro - fuzzy technique developed here consists of a pre - processor using backpropagation neural network followed by a fuzzy logic controller. Figure 6.1 depicts the neuro - fuzzy controller highlighting the details of the neurons with its inputs and output signal with fuzzy controller. The neural network used here also a backpropagation multilayer perceptron having six layers. The input layer has twelve neurons. The output layer has a single neuron meant to produce the setting load on prop. The output of the neural network i.e.1st estimated setting load is fed to the fuzzy controller along with the information concerning the various mine support geological parameters . The output of the fuzzy controller is to compute the setting load to be applied to the standing prop. From the previous chapter it was concluded that triangular membership function is the best among other membership function for this type of problem. Therefore triangular membership function is used in the fuzzy controller. Hybrid neuro-fuzzy systems are homogeneous and generally resemble neural network. The fuzzy system is interpreted as special kind of neural network. These systems can learn online and offline. Fuzzy sets can be regarded as weights whereas the input and output variables and the rules are modeled as neurons. The developed neuro - fuzzy technique is found to be most efficient for prediction of setting load to be given to the respective prop. Practical data verifications have been done with the simulation results to prove the authenticity of the developed neuro - fuzzy technique.

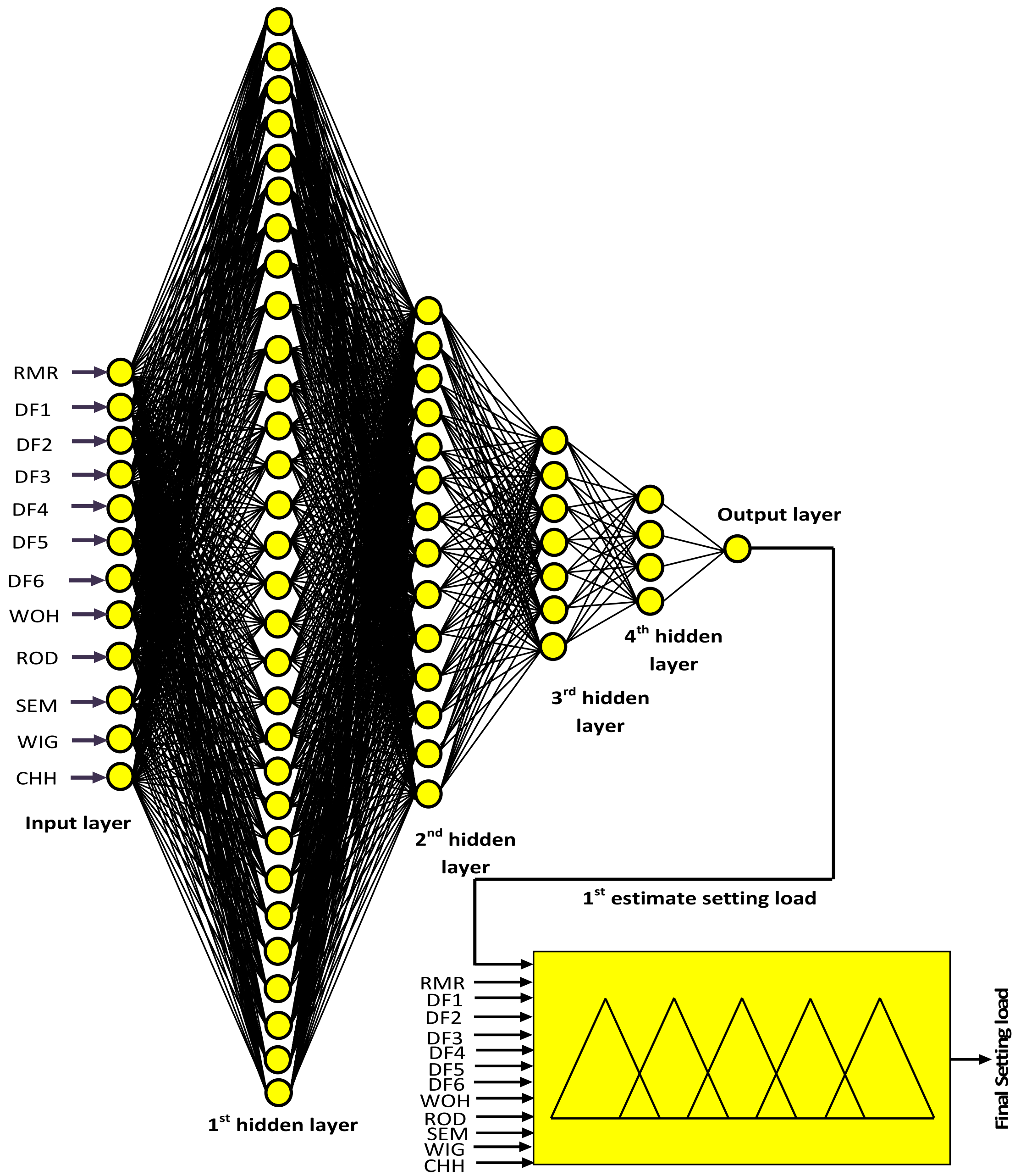


Figure 6.1 Neuro fuzzy controller

6.2.1 Result for Neuro-Fuzzy Hybrid Controller

Some of the fuzzy rules which contribute much are depicted for the above mentioned 12 parameters in table No.5.1. The estimated setting load from the neural network is fed to the fuzzy controller as 13th as target output parameter. Thus, final output setting load is obtained with neuro-fuzzy controller. By varying the various input parameters the required setting load on the first prop which is nearer to the blasting face is known. Setting load to be applied on the other prop may be known in similar fashion.

6.2.2 Simulation Results & Discussion

The series simulation tests have been conducted with the different parameters. The neuro – fuzzy controller is successfully giving the result by choosing any numbers of parameters out of the 12 variables. In this chapter, a new intelligent hybrid controller has been proposed for prediction of setting load to be applied on the nearest prop to the blasting face using neuro -fuzzy controller. It is more efficient than the other traditional reactive behaviour control and also easier to design and implement. In this technique with the help of trained neural net fuzzy rules linguistic variables were also represented. Setting load on the prop no.1 nearest to the blasting face was defuzzified and the estimated load obtained was compared with the practical setting load which was applied at mine site as shown in table 6.1.

TABLE 6.1Comparison of setting load simulated with neuro-fuzzy and real data

Serial Nos.	Parameters	Setting load applied on prop at mine site (tons)	Setting load on prop by neuro-fuzzy technique(tons)
1.	Twelve nos. of input parameters	9	9.01
2.		7	7
3.		10	10
4.		6	6.2
5.		10	9.9
6.		7	7.2
7.		8	8
8.		10	9.4
9.		6	5.9
10.		8	8.0

By simulation it is seen that setting load obtained from fuzzy logic technique is having average percentage variation 1.49 with real mine data.

6.3 Analysis of Fuzzy-Neuro Hybrid Controller

As mentioned above in this fuzzy – neuro controller the estimated setting load obtained as output from fuzzy logic controller is fed to the neural controller as target output parameters . Final output will be given by the neural network controller. The fuzzy – neuro technique developed here consists of a pre - processor fuzzy logic controller followed by a backpropagation based neural network. Figure 6.2 depicts the fuzzy – neuro controller highlighting the details of the 12 nos. of fuzzy input to the fuzzy controller and one output i.e. estimated setting load from fuzzy rules as shown in table 5.1. Output of the fuzzy controller as target outputs together with the 12 nos. of input in 12 neurons are fed to the neural network controller to get the final setting load to be applied on the props, neurons take on its inputs signal from fuzzy controller. The neural network used here considers a backpropagation multilayer perceptron having six layers consisting of one input layer, 4 hidden layers and one output layer. The input layer has thirteen neurons. The output layer has a single neuron to produce the setting load on prop. From the previous chapter it was concluded that triangular membership function is the best among other membership function for this type of problem. Therefore triangular membership function is used in the fuzzy controller. The developed fuzzy – neuro technique has been demonstrated in simulation mode, which depicts that the prop was applied with `the required load so that it does not dislodge after blasting of the working face. Amongst the techniques developed fuzzy-neuro is also one of the most efficient technique for prediction of setting load to be given to the respective prop. Practical data verifications have been done with the simulation results to prove the authenticity of the developed fuzzy - neuro technique.

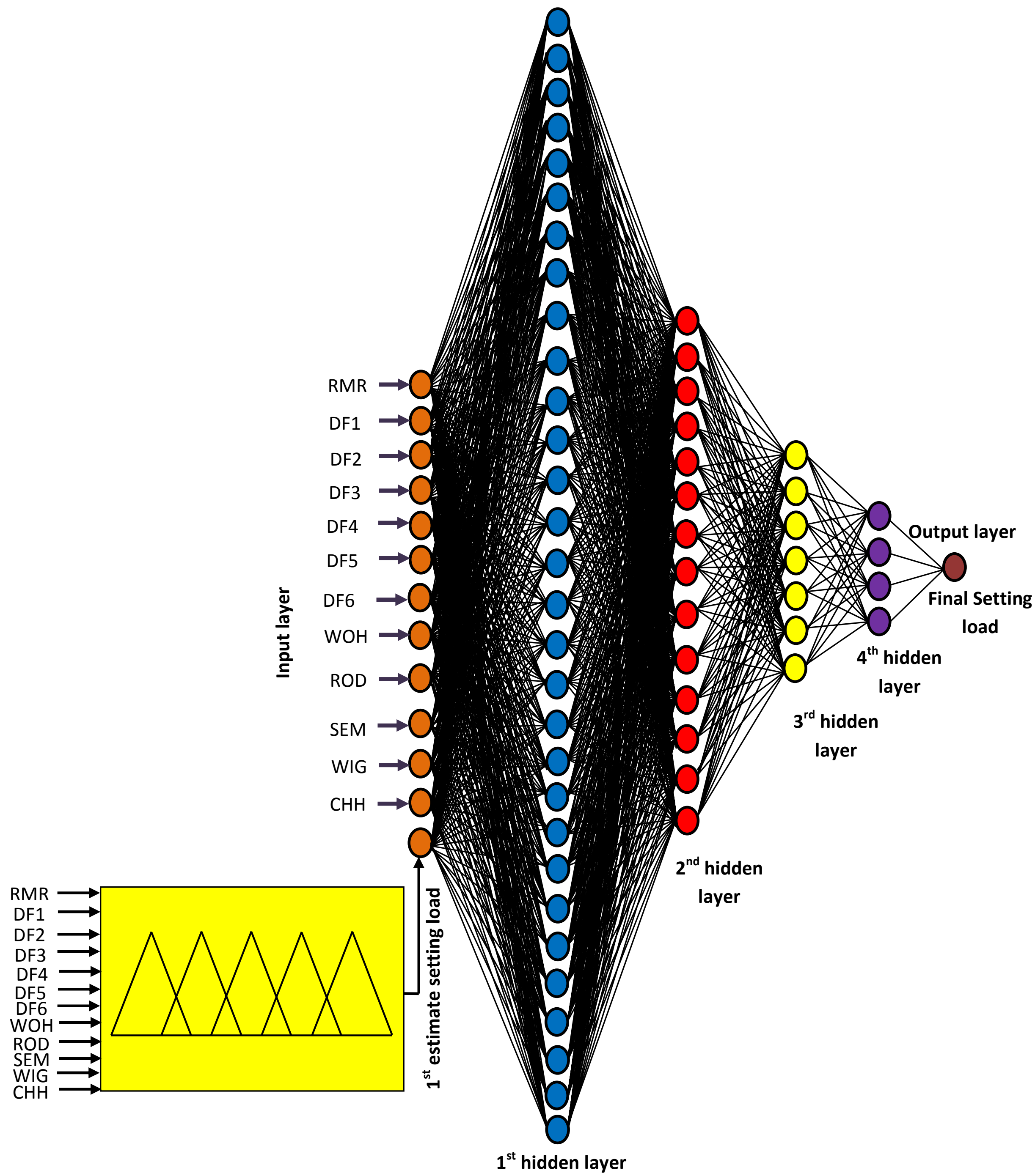


Figure.6.2 Fuzzy neural controller

6.3.1 Result for Fuzzy-Neuro Hybrid Controller

Some of the fuzzy rules which contribute much are depicted for the above mentioned 12 parameters in table no.5.1. The estimated setting load from the fuzzy controller is fed to the neural controller as target output parameter. Thus, final output setting load is obtained with fuzzy-neuro controller. By varying the various input parameters the required setting load on the first prop which is nearer to the blasting face is known. Setting load to be applied on the other prop may be known in similar fashion.

6.3.2 Simulation Results & Discussion

The series simulation tests have been conducted with the different parameters. The fuzzy –neuro controller is successfully giving the result by choosing any numbers parameters out of the 12 variables. In this technique, a new intelligent controller has been proposed for prediction of setting load to be applied on the nearest prop to the blasting face using fuzzy logic. It is more efficient than the other traditional reactive behaviour control and also easier to design and implement. Final setting load after simulation has been depicted in table 6.2 which is at par with the practical setting load applied at the mine site.

TABLE 6.2Comparison of setting load simulated with fuzzy-neuro and real data

Serial Nos.	Parameters	Setting load applied on prop at mine site (tons)	Setting load on prop by fuzzy-neuro technique(tons)
1.	Twelve nos. of input parameters	9	9.02
2.		7	7.02
3.		10	10
4.		6	6.3
5.		10	9.8
6.		7	7.2
7.		8	8
8.		10	10
9.		6	5.9
10.		8	8.5

By simulation it is seen that setting load obtained from fuzzy logic technique is having average percentage variation 1.82 with real mine data.

Simulated results are at par with the practical setting load applied at mine site.

6.4 Summary

In this chapter mine support parameters were simulated by neuro-fuzzy hybrid controller as well as fuzzy-neural hybrid controller. The results were compared with the practical real data from the mine and were found most efficient and suitable for mine site applications. Other hybrid models were also developed by some researchers. Hidden Markov Model (HMM) and a neural network (NN) were developed by a researcher (100) for probability based determination of underground tunnel geology. Ground conditions of a tunneling project were predicted with the help of Support Vector Machines (SVM) and artificial neural network (101). With the help of Neuro-fuzzy model ground subsidence hazard maps were created to show the hazards distribution (102). Some researchers (103) have modeled the underground mine tunnel diameter convergence to prevent deadly hazards. Next chapter deals with analysis of rule based technique for estimation setting load on prop.

CHAPTER 7

RULE BASED HYBRID CONTROLLER

7 Rule Based Hybrid Controller

This chapter describes the rule-based technique. Firstly, a set of rules for applying load is extracted from the examples. Then, these rules are used on their own to estimate the required load on prop or they can be used in conjunction with other hybrid techniques. All such possibilities are analysed and explained below.

7.1 Introduction

In a rule based system, the knowledge of the environment is stated confirm in the form of rule. These are the major types of knowledge representation formalities used in expert systems. There are three main components of typical rule based system i.e. the working memory, the rule base and the inference engine. The working memory contains informations about the particular instant of the problem being solved. The rule base is a set of rules, which represent the problem solving knowledge about the domain. A rule contains a set of conditions (antecedents) and a set of conclusions (consequents). The inference uses the rule base and the working memory to derive new information. The rule base controller is basically a look up table technique for representing complex non-linear system. A correct rule could be made depending upon the mine support parameters which in turn depends upon the geology of the mine. All rule –based systems need a control strategy to decide conflicts between two or more applicable rules. Mostly, Environmental conditions can affect the entire rule base. Instead of modifying each rule individually ,we investigate the possibility of modifying all the rules at once with the help of Clematine rule base software [104].

7.2 Analysis of Rule Based Controller

Optimisation of setting load applied to the prop nearest to the blasting face in bord and pillar mining using rule based technique is presented in this research work. Firstly, a set of variables rules are extracted from the data base through ‘C5”algorithm. The rules are used on their own to estimate the setting load on the prop. Rules are also combined together which gives rise to a rule based technique for predicting setting load to be applied on the prop. The rules used can be used on their own or they can be combined with another tool to produce a hybrid control technique. The rule base used for estimation of setting load on prop is generated by induction from examples. Approximately one thousand examples are fed to C5. C5 is a rule induction programme within the data mining software package [105]. C5 employs a sophisticated divide and conquer technique originating from ID3 family of algorithms [106].

The examples present the situations during different set of mining having different input parameters which changes the setting load to be applied on the prop. Each example is consisting of twelve input parameters specifying the RMR, Different distances of subsequent prop from the first prop from the face, working height, rock density, seam thickness, width of gallery and charge per hole and an output element setting load on prop. Some of the rules are mentioned below in table 7.1

Table 7.1 Data rules for ruled based techniques

Sl. No.	RMR	Distance of first prop from the face(DF1) (m)	DF2	DF3	DF4	DF5	DF6	Working height (m)	Rock density(g/cc)	Seam thickness (m)	Width of gallery(m)	Charge per hole(g)	Setting load(T)
1	40	0.4	1.0	1.8	2.4	3.0	4.6	2.4	2.2	3.4	4.2	400	9
2	48	0.4	1.0	1.8	2.2	3.2	4.0	4.5	2.2	3.4	4.2	400	8
3	48	0.4	1.0	1.8	2.2	3.0	4.0	4.2	2.2	3.4	4.2	400	8
4	46	0.4	1.0	1.8	2.2	3.0	4.0	4.0	2.3	3.8	4.0	450	8
5	50	0.4	1.0	1.8	2.6	3.0	4.0	4.0	2.2	3.4	4.2	400	7
6	46	0.4	1.0	1.8	2.2	3.4	4.4	4.5	2.2	3.4	4.2	400	8
7	50	0.6	1.0	1.8	2.8	3.0	4.4	4.5	2.2	3.6	4.5	400	7
8	52	0.6	1.0	1.8	2.8	3.0	4.4	4.5	2.2	3.4	4.2	450	7
9	51	0.6	1.0	1.8	2.8	3.4	4.4	4.4	2.4	3.4	4.5	450	6
10	49	0.7	0.9	1.8	2.8	3.4	4.4	4.4	2.2	3.4	4.2	450	7
11	49	0.5	1.0	1.4	2.8	3.4	4.4	4.4	2.2	3.4	4.2	400	7
12	44	0.8	1.0	1.8	2.2	3.4	4.6	4.4	2.2	3.4	4.2	400	8
13	52	0.8	1.0	1.8	2.2	3.4	4.6	4.4	2.2	3.4	4.2	400	6
14	40	0.8	1.0	1.8	2.2	3.0	4.6	4.2	2.2	3.4	4.5	400	9
15	56	0.8	1.0	1.8	2.2	3.0	4.6	4.2	2.2	3.8	4.2	400	6
16	58	0.8	1.0	1.8	2.2	3.0	4.6	4.2	2.2	3.4	4.2	500	6
17	58	0.6	1.2	1.4	2.4	3.0	4.0	4.2	2.2	3.4	4.2	500	6

18	58	0.8	1.2	1.8	2.2	3.0	4.0	4.0	2.4	3.7	4.2	400	6
19	58	0.8	1.2	1.8	2.2	3.0	4.0	4.0	2.2	3.7	4.2	400	6
20	58	0.8	1.2	1.8	2.2	3.6	4.2	4.2	2.2	3.7	4.5	400	6
21	39	0.8	1.0	1.8	2.5	3.0	4.0	4.2	2.2	3.4	4.2	400	9
22	40	0.8	1.2	1.6	2.2	3.0	4.0	2.8	2.2	3.4	4.2	550	9
23	44	0.8	1.0	1.8	2.2	3.6	4.4	2.8	2.2	3.6	4.2	400	8
24	43	0.4	1.0	1.8	2.7	3.6	4.3	2.8	2.2	4.0	4.2	400	8
25	48	0.8	1.0	1.8	2.2	3.6	4.5	4.4	2.2	4.2	4.2	500	7
26	49	0.8	1.0	1.8	2.2	3.0	4.6	3.0	2.2	3.4	4.2	450	7
27	44	0.8	1.0	1.8	2.3	3.0	4.0	3.0	2.2	3.4	4.2	400	8
28	56	0.8	1.0	1.8	2.2	3.4	4.0	3.2	2.2	3.4	4.2	400	6
29	45	0.8	1.0	2.2	2.2	3.4	4.1	3.2	2.2	3.4	4.2	400	8
30	56	0.8	1.1	1.8	2.2	2.8	4.0	4.4	2.2	4.5	4.2	550	6
31	38	0.8	1.0	1.8	2.6	3.0	4.0	4.5	2.2	3.4	4.2	600	10
32	38	0.6	1.2	1.8	2.2	3.0	4.0	3.2	2.2	3.4	4.2	400	10
33	38	0.8	1.0	1.8	2.2	3.0	4.0	4.2	2.5	3.4	4.2	400	10
34	38	0.8	1.0	1.8	2.2	3.0	4.2	4.2	2.2	4.4	4.2	400	10
35	39	0.8	1.0	1.8	2.6	3.0	4.0	4.0	2.2	3.4	4.2	400	9
36	38	0.8	1.0	1.8	2.2	2.6	4.0	4.5	2.2	3.4	4.2	400	9

37	40	0.8	1.0	1.8	2.2	3.0	4.0	4.2	2.2	3.4	4.2	500	9
38	40	0.8	1.0	1.9	2.2	2.6	4.2	4.0	2.2	3.4	4.5	450	9
39	40	0.5	1.0	1.8	3.0	3.6	4.0	3.8	2.2	3.4	4.2	400	9
40	40	0.8	1.2	1.8	2.2	3.0	4.0	3.6	2.2	4.7	4.2	400	9
41	40	0.8	1.0	1.6	2.2	3.0	4.0	3.4	2.2	3.4	4.2	400	9
42	51	0.8	1.0	1.8	2.2	3.0	4.0	2.8	2.2	3.4	4.0	400	8
43	51	0.8	1.4	1.8	2.2	3.0	4.2	2.6	2.2	3.4	4.2	400	8
44	52	0.8	1.4	1.4	2.8	3.0	4.0	2.4	2.2	3.4	4.2	400	8
45	52	0.8	1.0	1.8	2.2	3.8	4.0	2.8	2.3	4.8	4.2	400	8
46	54	0.8	1.0	1.8	2.2	3.0	4.0	4.4	2.2	3.4	4.2	400	7
47	54	0.8	1.4	1.8	2.2	3.0	4.0	4.2	2.2	3.4	4.2	400	7
48	53	0.8	1.0	1.8	2.0	3.0	4.0	4.0	2.2	3.4	4.2	400	7
49	53	0.8	1.0	1.8	2.2	3.4	4.0	4.0	2.2	3.4	4.2	400	8
50	53	0.8	1.2	2-0	2.4	3.0	4.0	3.0	2.2	3.4	4.2	500	8

Rule 2 described that if the RMR (Rock Mass Rating) of the rock is 48 and distance of the first prop from the face is 0.4 meter, distances of the 2^{nd},3^{rd},4^{th},5^{th},and 6^{th} prop from the face are respectively 1,1.8,2.2,3.2 and 4 m, working height 4.5m, rock density 2.2g/cc, seam thickness 3.4m, width of gallery 4.2m, charge per hole 400g, then setting load required to the prop is 8 tons.

In this exercise 10,000 situations are fed to C5. From these situation C5 yields 54 rules. Out of 54 rules 2 rules are listed below.

Rule1

If (RMR > 40) and (distance of the first prop from the face <=0.6m)and (distance of the 2^{nd} prop from the face<=1m)and (distance of the 3^{rd} prop from the face<=1)and(distance of the 4^{th} prop from the face<=1)and(distance of the 5^{th} prop from the face<=1)and(distance of the 6^{th} prop from the face<=1) and (working height>3m)and(rock density >=2.2g/cc) and (seam thickness>=3.0m) and (width of gallery <=4.2m)and (charge per hole >=400g)

Then setting load to be applied on prop = 7Ton

Rule2

If (RMR >= 40) and (distance of the first prop from the face <=0.6m)and (distance of the 2^{nd} prop from the face=1.2m)and (distance of the 3^{rd} prop from the face>=1.8m)and(distance of the 4^{th} prop from the face<=2m)and(distance of the 5^{th} prop from the face<=2.8)and(distance of the 6^{th} prop from the face<=3m) and (working height<3m)and(rock density >=2.2g/cc) and (seam thickness>=3.0m) and (width of gallery <=4.2m)and (charge per hole >=400g)

Then setting load to be applied on prop = 8Ton

In addition to that other rules are obtained like If (RMR > 40) and (distance of the first prop from the face <=0.6m)and (distance of the 2^{nd} prop from the face<=1m)and (distance of the 3^{rd} prop from the face<=1.4)and(distance of the 4^{th} prop from the face<=2)and(distance of the 5^{th} prop from the face<=2.6)and(distance of the 6^{th} prop from the face<=3.2) and (working height=>3m)and(rock density >=2.4g/cc) and (seam thickness>=3.0m) and (width of gallery <=4.2m)and (charge per hole >=400g)

Then setting load to be applied on prop = 8Ton,

If (RMR < 40) and (distance of the first prop from the face <=0.7m)and (distance of the 2^{nd} prop from the face<=1.4m)and (distance of the 3^{rd} prop from the face<=1.8m)and(distance of the 4^{th} prop from the face<=2.0m)and(distance of the 5^{th} prop from the face<=2.8m)and(distance of the 6^{th} prop from the face<=3.3) and (working height>2.8m)and(rock density >=2.4g/cc) and (seam thickness>=3.4m) and (width of gallery <=3.8m)and (charge per hole >=450g)

Then setting load to be applied on prop = 9Ton

If (RMR > =45) and (distance of the first prop from the face <=0.6m)and (distance of the 2^{nd} prop from the face<=1m)and (distance of the 3^{rd} prop from the face<=1.8m)and(distance of the 4^{th} prop from the face<=2m)and(distance of the 5^{th} prop from the face<=2.4)and(distance of the 6^{th} prop from the face<=3.0m) and (working height>3.8m)and(rock density >=2.8g/cc) and (seam thickness>=3.0m) and (width of gallery <=4.2m)and (charge per hole >=500g)

Then setting load to be applied on prop = 9Ton,

If (RMR >= 50) and (distance of the first prop from the face <=0.8m)and (distance of the 2^{nd} prop from the face<=1m)and (distance of the 3^{rd} prop from the face<=1.4)and(distance of the 4^{th} prop from the face<=2.0m)and(distance of the 5^{th} prop from the face<=2.4)and(distance of the 6^{th} prop from the face<=2.8) and (working height>=3.6m)and(rock density >=2.6g/cc) and (seam thickness>=3.8m) and (width of gallery <=4.0m)and (charge per hole >=400g)

Then setting load to be applied on prop = 8Ton

If (RMR >= 50) and (distance of the first prop from the face <=0.8m)and (distance of the 2nd prop from the face<=1m)and (distance of the 3rd prop from the face<=1.4)and(distance of the 4th prop from the face<=2.0m)and(distance of the 5th prop from the face<=2.4)and(distance of the 6th prop from the face<=2.8) and (working height>=3.6m)and(rock density >=2.6g/cc) and (seam thickness>=3.8m) and (width of gallery <=4.0m)and (charge per hole >=500g)

Then setting load to be applied on prop = 9Ton

If (RMR >= 55) and (distance of the first prop from the face <=0.8m)and (distance of the 2nd prop from the face<=1m)and (distance of the 3rd prop from the face<=1.4)and(distance of the 4th prop from the face<=2.0m)and(distance of the 5th prop from the face<=2.4)and(distance of the 6th prop from the face<=2.8) and (working height>=3.6m)and(rock density >=2.6g/cc) and (seam thickness>=3.8m) and (width of gallery <=4.0m)and (charge per hole >=500g)

Then setting load to be applied on prop = 7Tons

If (RMR >= 55) and (distance of the first prop from the face <=0.8m)and (distance of the 2nd prop from the face<=1m)and (distance of the 3rd prop from the face<=1.4)and(distance of the 4th prop from the face<=2.0m)and(distance of the 5th prop from the face<=2.4)and(distance of the 6th prop from the face<=2.8) and (working height>=3.6m)and(rock density >=2.6g/cc) and (seam thickness>=3.8m) and (width of gallery <=3.0m)and (charge per hole >=550g)

Then setting load to be applied on prop = 8Ton

If (RMR >= 55) and (distance of the first prop from the face <=0.8m)and (distance of the 2nd prop from the face<=1m)and (distance of the 3rd prop from the face<=1.4)and(distance of the 4th prop from the face<=2.0m)and(distance of the 5th prop from the face<=2.4)and(distance of the 6th prop from the face<=2.8) and (working height>=3.6m)and(rock density >=2.4g/cc) and (seam thickness>=3.8m) and (width of gallery <=3.0m)and (charge per hole >=550g)

Then setting load to be applied on prop = 8Ton

If (RMR >= 58) and (distance of the first prop from the face <=0.8m)and (distance of the 2^{nd} prop from the face<=1m)and (distance of the 3^{rd} prop from the face<=1.4)and(distance of the 4^{th} prop from the face<=2.0m)and(distance of the 5^{th} prop from the face<=2.4)and(distance of the 6^{th} prop from the face<=2.8) and (working height>=3.6m)and(rock density >=2.4g/cc) and (seam thickness>=3.8m) and (width of gallery <=3.0m)and (charge per hole >=550g)

Then setting load to be applied on prop = 7Ton

If (RMR >= 58) and (distance of the first prop from the face <=0.8m)and (distance of the 2^{nd} prop from the face<=1m)and (distance of the 3^{rd} prop from the face<=1.4)and(distance of the 4^{th} prop from the face<=2.8m)and(distance of the 5^{th} prop from the face<=2.4)and(distance of the 6^{th} prop from the face<=2.8) and (working height>=4.0m)and(rock density >=2.4g/cc) and (seam thickness>=3.8m) and (width of gallery <=3.0m)and (charge per hole >=550g)

Then setting load to be applied on prop = 9Ton

If (RMR >= 52) and (distance of the first prop from the face <=0.8m)and (distance of the 2nd prop from the face<=1m)and (distance of the 3rd prop from the face<=1.4)and(distance of the 4th prop from the face<=2.8m)and(distance of the 5th prop from the face<=2.4)and(distance of the 6th prop from the face<=2.8) and (working height>=4.5m)and(rock density >=2.4g/cc) and (seam thickness>=3.8m) and (width of gallery <=3.0m)and (charge per hole >=550g)

Then setting load to be applied on prop = 10Ton

If (RMR >= 42) and (distance of the first prop from the face <=0.8m)and (distance of the 2nd prop from the face<=1m)and (distance of the 3rd prop from the face<=1.4)and(distance of the 4th prop from the face<=2.8m)and(distance of the 5th prop from the face<=2.4)and(distance of the 6th prop from the face<=2.8) and (working height>=4.5m)and(rock density >=2.4g/cc) and (seam thickness>=3.8m) and (width of gallery <=3.0m)and (charge per hole >=600g)

Then setting load to be applied on prop = 10Ton

If (RMR >= 45) and (distance of the first prop from the face <=0.8m)and (distance of the 2^{nd} prop from the face<=1m)and (distance of the 3^{rd} prop from the face<=1.4)and(distance of the 4^{th} prop from the face<=2.8m)and(distance of the 5^{th} prop from the face<=2.4)and(distance of the 6^{th} prop from the face<=2.8) and (working height>=4.5m)and(rock density >=2.8g/cc) and (seam thickness>=3.8m) and (width of gallery <=3.6m)and (charge per hole >=600g)

Then setting load to be applied on prop = 9Ton

If (RMR >= 45) and (distance of the first prop from the face <=0.8m)and (distance of the 2^{nd} prop from the face<=1m)and (distance of the 3^{rd} prop from the face<=1.2)and(distance of the 4^{th} prop from the face<=1.8m)and(distance of the 5^{th} prop from the face<=2.4)and(distance of the 6^{th} prop from the face<=2.8) and (working height>=4.5m)and(rock density >=2.8g/cc) and (seam thickness>=3.8m) and (width of gallery <=3.6m)and (charge per hole >=600g)

Then setting load to be applied on prop = 9Ton

If (RMR >= 58) and (distance of the first prop from the face <=0.8m)and (distance of the 2nd prop from the face<=1m)and (distance of the 3rd prop from the face<=1.2)and(distance of the 4th prop from the face<=1.8m)and(distance of the 5th prop from the face<=2.4)and(distance of the 6th prop from the face<=2.8) and (working height>=4.5m)and(rock density >=2.8g/cc) and (seam thickness>=3.8m) and (width of gallery <=3.6m)and (charge per hole >=600g)

Then setting load to be applied on prop = 6Ton

If (RMR >= 58) and (distance of the first prop from the face <=0.8m)and (distance of the 2nd prop from the face<=1m)and (distance of the 3rd prop from the face<=1.2)and(distance of the 4th prop from the face<=1.8m)and(distance of the 5th prop from the face<=2.2)and(distance of the 6th prop from the face<=2.8) and (working height>=4.5m)and(rock density >=2.8g/cc) and (seam thickness>=3.8m) and (width of gallery <=3.6m)and (charge per hole >=600g)

Then setting load to be applied on prop = 7Ton

If (RMR >= 58) and (distance of the first prop from the face <=0.8m)and (distance of the 2nd prop from the face<=1m)and (distance of the 3rd prop from the face<=1.2)and(distance of the 4th prop from the face<=1.8m)and(distance of the 5th prop from the face<=2.2)and(distance of the 6th prop from the face<=3.0m) and (working height>=4.0m)and(rock density >=2.8g/cc) and (seam thickness>=3.8m) and (width of gallery <=3.6m)and (charge per hole >=600g)

Then setting load to be applied on prop = 6Ton

If (RMR >= 58) and (distance of the first prop from the face <=0.8m)and (distance of the 2nd prop from the face<=1m)and (distance of the 3rd prop from the face<=1.2)and(distance of the 4th prop from the face<=1.8m)and(distance of the 5th prop from the face<=2.2)and(distance of the 6th prop from the face<=3.0m) and (working height>=4.0m)and(rock density >=2.8g/cc) and (seam thickness>=3.8m) and (width of gallery <=3.6m)and (charge per hole >=500g)

Then setting load to be applied on prop = 6Ton

If (RMR >= 58) and (distance of the first prop from the face <=0.8m)and (distance of the 2^{nd} prop from the face<=1m)and (distance of the 3^{rd} prop from the face<=1.2)and(distance of the 4^{th} prop from the face<=1.8m)and(distance of the 5^{th} prop from the face<=2.2)and(distance of the 6^{th} prop from the face<=3.0m) and (working height>=3.0m)and(rock density >=2.8g/cc) and (seam thickness>=3.8m) and (width of gallery <=2.8m)and (charge per hole >=500g)

Then setting load to be applied on prop = 7Ton

If (RMR >= 58) and (distance of the first prop from the face <=0.8m)and (distance of the 2^{nd} prop from the face<=1m)and (distance of the 3^{rd} prop from the face<=1.2)and(distance of the 4^{th} prop from the face<=1.8m)and(distance of the 5^{th} prop from the face<=2.2)and(distance of the 6^{th} prop from the face<=3.0m) and (working height>=3.0m)and(rock density >=2.8g/cc) and (seam thickness>=3.8m) and (width of gallery <=2.8m)and (charge per hole >=500g)

Then setting load to be applied on prop = 7Ton

If (RMR >= 50) and (distance of the first prop from the face <=0.7m)and (distance of the 2nd prop from the face<=1m)and (distance of the 3rd prop from the face<=1.4)and(distance of the 4th prop from the face<=1.8m)and(distance of the 5th prop from the face<=2.2)and(distance of the 6th prop from the face<=3.0m) and (working height>=3.0m)and(rock density >=2.8g/cc) and (seam thickness>=3.8m) and (width of gallery <=2.8m)and (charge per hole >=500g)

Then setting load to be applied on prop = 8Ton

If (RMR >= 52) and (distance of the first prop from the face <=0.7m)and (distance of the 2nd prop from the face<=1m)and (distance of the 3rd prop from the face<=1.4)and(distance of the 4th prop from the face<=1.8m)and(distance of the 5th prop from the face<=2.2)and(distance of the 6th prop from the face<=3.0m) and (working height>=3.0m)and(rock density >=2.8g/cc) and (seam thickness>=3.8m) and (width of gallery <=2.4m)and (charge per hole >=500g)

Then setting load to be applied on prop = 7Ton

If (RMR >= 52) and (distance of the first prop from the face <=0.7m)and (distance of the 2^{nd} prop from the face<=1.2m)and (distance of the 3^{rd} prop from the face<=1.4)and(distance of the 4^{th} prop from the face<=2.0m)and(distance of the 5^{th} prop from the face<=2.2)and(distance of the 6^{th} prop from the face<=3.0m) and (working height>=3.0m)and(rock density >=2.8g/cc) and (seam thickness>=3.8m) and (width of gallery <=2.4m)and (charge per hole >=500g)

Then setting load to be applied on prop = 7Ton

If (RMR >= 48) and (distance of the first prop from the face <=0.7m)and (distance of the 2^{nd} prop from the face<=1.2m)and (distance of the 3^{rd} prop from the face<=1.4)and(distance of the 4^{th} prop from the face<=2.0m)and(distance of the 5^{th} prop from the face<=2.2)and(distance of the 6^{th} prop from the face<=3.0m) and (working height>=3.0m)and(rock density >=2.2g/cc) and (seam thickness>=3.8m) and (width of gallery <=2.4m)and (charge per hole >=500g)

Then setting load to be applied on prop = 8Ton

If (RMR >= 48) and (distance of the first prop from the face <=0.7m)and (distance of the 2nd prop from the face<=1.2m)and (distance of the 3rd prop from the face<=1.4)and(distance of the 4th prop from the face<=2.0m)and(distance of the 5th prop from the face<=2.2)and(distance of the 6th prop from the face<=3.0m) and (working height>=3.0m)and(rock density >=2.2g/cc) and (seam thickness>=3.8m) and (width of gallery <=2.4m)and (charge per hole >=600g)

Then setting load to be applied on prop = 9Ton,

If (RMR >= 48) and (distance of the first prop from the face <=0.7m)and (distance of the 2nd prop from the face<=1.2m)and (distance of the 3rd prop from the face<=1.4)and(distance of the 4th prop from the face<=2.0m)and(distance of the 5th prop from the face<=2.2)and(distance of the 6th prop from the face<=3.2m) and (working height>=3.0m)and(rock density >=2.2g/cc) and (seam thickness>=3.4m) and (width of gallery <=2.4m)and (charge per hole >=600g)

Then setting load to be applied on prop = 10Ton

If (RMR >= 48) and (distance of the first prop from the face <=0.7m)and (distance of the 2nd prop from the face<=1.2m)and (distance of the 3rd prop from the face<=1.4)and(distance of the 4th prop from the face<=2.0m)and(distance of the 5th prop from the face<=2.2)and(distance of the 6th prop from the face<=3.2m) and (working height>=3.0m)and(rock density >=2.2g/cc) and (seam thickness>=3.4m) and (width of gallery <=2.4m)and (charge per hole >=600g)

Then setting load to be applied on prop = 10Ton,

If (RMR >= 42) and (distance of the first prop from the face <=0.7m)and (distance of the 2nd prop from the face<=1.2m)and (distance of the 3rd prop from the face<=1.4)and(distance of the 4th prop from the face<=2.0m)and(distance of the 5th prop from the face<=2.2)and(distance of the 6th prop from the face<=3.2m) and (working height>=2.8m)and(rock density >=2.2g/cc) and (seam thickness>=3.4m) and (width of gallery <=2.4m)and (charge per hole >=600g)

Then setting load to be applied on prop = 9Ton

If (RMR >= 48) and (distance of the first prop from the face <=0.7m)and (distance of the 2nd prop from the face<=1.2m)and (distance of the 3rd prop from the face<=1.4)and(distance of the 4th prop from the face<=2.0m)and(distance of the 5th prop from the face<=2.2)and(distance of the 6th prop from the face<=3.2m) and (working height>=3.0m)and(rock density >=2.2g/cc) and (seam thickness>=2.9m) and (width of gallery <=4.2m)and (charge per hole >=600g)

Then setting load to be applied on prop = 9Ton

TABLE 7.2 Comparison of setting load simulated with rule based technique and real data

Serial Nos.	Parameters	Setting load applied on prop at mine site (tons)	Setting load on prop by rule based technique(tons)
1.	Twelve nos. of input parameters	9	9.3
2.		7	7.1
3.		10	10
4.		6	5.9
5.		10	10
6.		7	7.8
7.		8	8.2
8.		10	10
9.		6	5.8
10.		8	8.0

By simulation it is seen in table 7.2 that setting load obtained from rule based technique is having average percentage variation 2.36 with real mine data.

7.3 Analysis of Rule Based Fuzzy Controller

The above mentioned set of rules represents the core of a pure rule-based controller. This set of rules can also be combined with other tools to yield a hybrid controller. Because of that the fuzzy technique has proved to be one of the effective techniques used, it will be employed in conjunction with the derived rule set to form a rule-based fuzzy controller. The resulting architecture is shown in Figure 7.1. This is similar to the neuro-fuzzy controller of Chapter 6 except that the pre-processor is now replaced by the rule set. The interim output i.e. target setting load will be fed to the fuzzy controller to get the final setting load on prop.

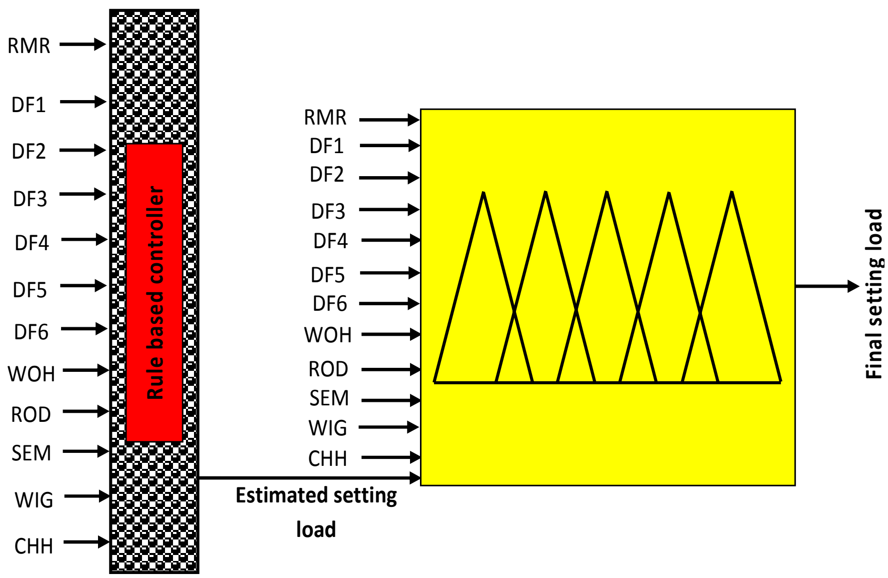


Figure 7.1 Rule based fuzzy controller

Table 7.3 Comparison of setting load simulated with Rule Based Fuzzy and real data

Serial Nos.	Parameters	At mine site(tons)	By Rule Based Fuzzy technique(tons)
1.	Setting load on first prop from face	9	9
2.		7	7.2
3.		10	9.9
4.		6	6
5.		10	10
6.		7	7.1
7.		8	8.0
8.		10	9.05
9.		6	6.3
10.		8	8

By simulation it is seen that setting load obtained from rule based fuzzy technique is having average percentage variation 1.8 with real mine data.

7.4 Analysis of Rule Based Neuro Controller

The above mentioned set of rules represents the core of a pure rule-based controller. This set of rules can also be combined with other tools to yield a hybrid controller. Because the neural network technique has proved to be one of the effective tool to handle the problem given, it will be employed in association with the derived rule set to form a rule-based neuro- controller. The resulting architecture is shown in Figure 7.2. This is similar to the fuzzy -neuro controller of Chapter 6 except that the pre-processor is now replaced by the rule set. The output of the rule based controller will be fed to the neural network to find out the final setting load on prop.

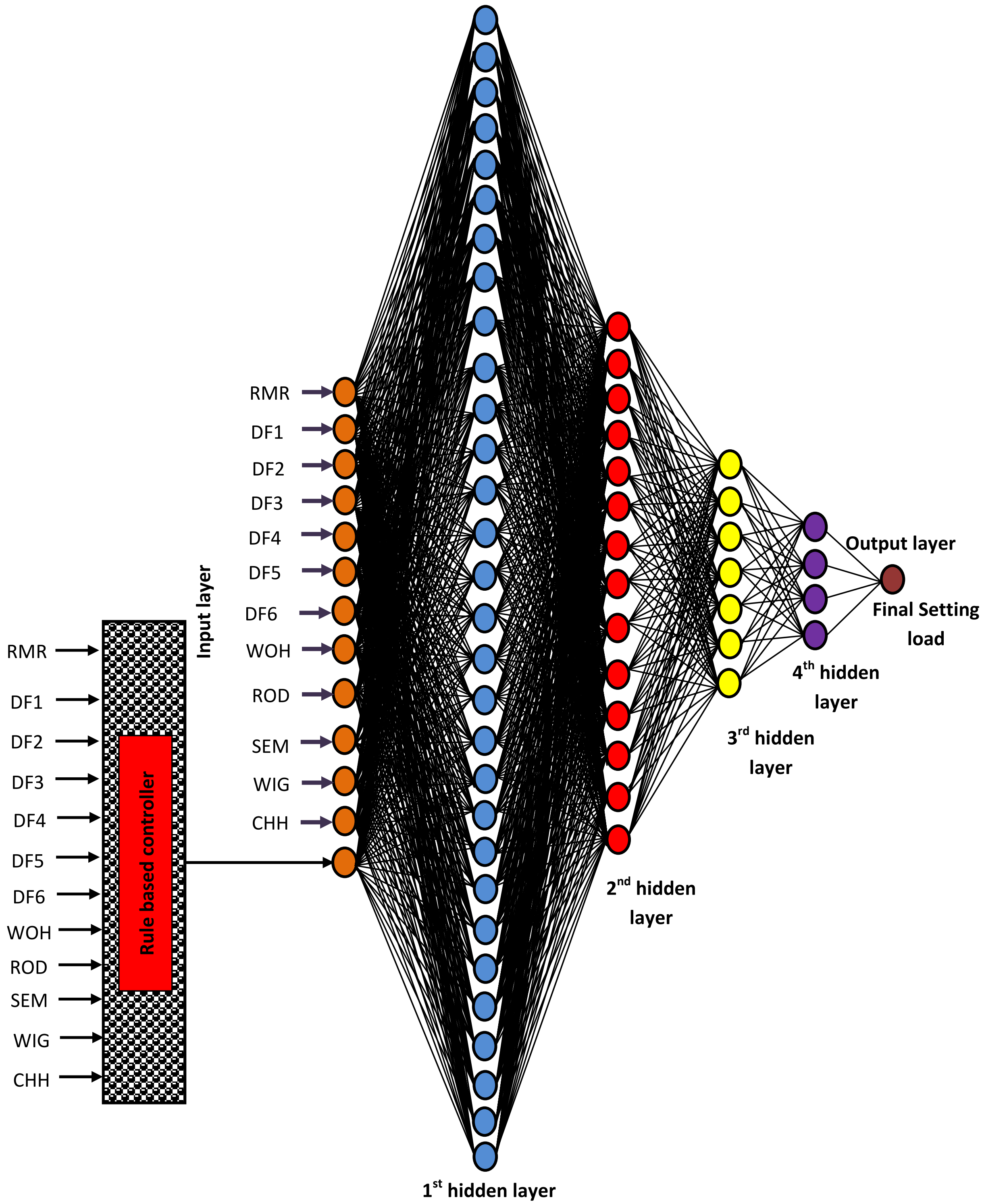


Figure 7.2 Rule based neural controller

Table 7.4 Comparison of setting load simulated Rule Based Neuro and real data

Serial Nos.	Parameters	At mine site(tons)	By Rule Based Neuro technique(tons)
1.	Setting load on first prop from face	9	9.8
2.		7	7
3.		10	10.4
4.		6	6
5.		10	10
6.		7	6.9
7.		8	8.05
8.		10	9.99
9.		6	6.0
10.		8	8.0

By simulation it is seen that setting load obtained from rule based neuro technique is having average percentage variation 1.5 with real mine data.

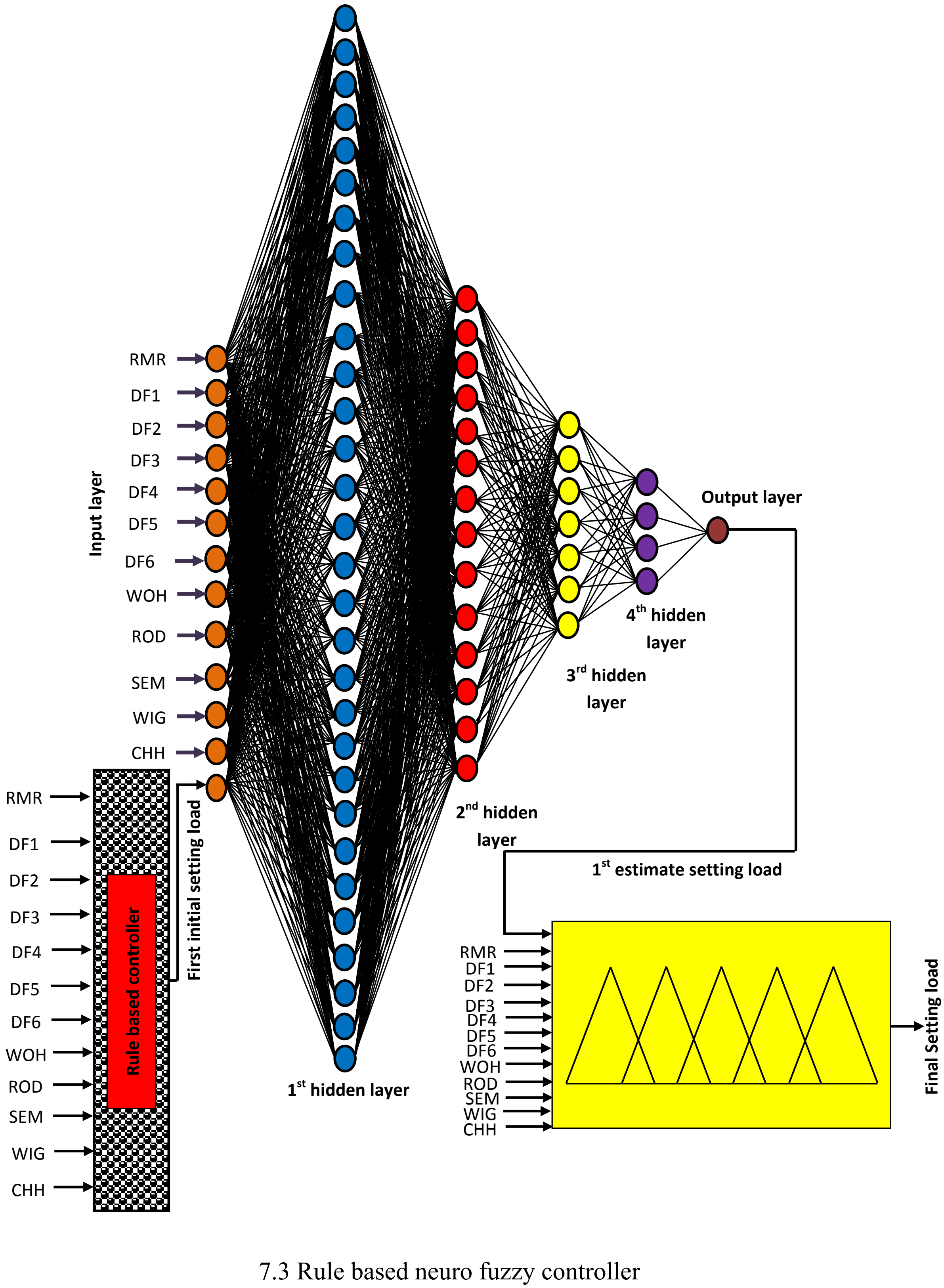
7.5 Analysis of Rule Based Neuro-Fuzzy Controller

The above mentioned set of rules represents the prime part of a pure rule-based controller. This set of rules can also be combined with other tools to yield a hybrid controller. Because the neuro-fuzzy network technique has proved to be one of the most effective techniques to handle the complex engineering problem, it will be employed in conjunction with the derived rule set to form a rule-based neuro-fuzzy controller. The resulting architecture is shown in Figure 7.3. This is similar to the neuro -fuzzy controller of Chapter 6 except that the pre-processor is now here rule base for neuro –fuzzy controller. Here output of the rule based controller will be the first estimate of setting load . This target loads again fed to the neural controller and output of this very controller i.e. second estimate of setting load will be then fed to the fuzzy controller to get the final setting load.

Table 7.5 Comparison of setting load simulated with RBNF and real data

Serial Nos.	Parameters	At mine site(tons)	By Rule Based Neuro-Fuzzy technique(tons)
1.	Setting load on first prop from face	9	9.07
2.		7	7.01
3.		10	9.9
4.		6	5.98
5.		10	9.98
6.		7	7.0
7.		8	8.0
8.		10	10
9.		6	5.95
10.		8	8.0

By simulation it is seen that setting load obtained from Rule Based Neuro- Fuzzy (RBNF) technique is having average percentage variation 0.227 with real mine data.



7.3 Rule based neuro fuzzy controller

7.6 Analysis of Rule Based Fuzzy-Neuro Controller

The above mentioned set of rules represents the main part of a pure rule-based controller. This set of rules can also be combined with other tools to make a more effective and efficient hybrid controller. Because the fuzzy-neuro is itself a hybrid technique and has proved to be one of the most effective methods to handle the complex engineering problem, it will be employed in conjunction with the derived set of rules to form a rule-based neuro-fuzzy controller. The resulting architecture is shown in Figure 7.4. This is similar to the fuzzy-neuro controller of Chapter 6 except that the pre-processor is now here rule base for fuzzy-neuro controller. Here output of the rule based controller will be the first estimate of setting load. This target loads again fed to the fuzzy controller and output of this controller i.e. second estimate of setting load will be again fed to the neural network to get the final setting load.

Table 7.6 Comparison of setting load simulated with RBFN and real data

Serial Nos.	Parameters	At mine site(tons)	By Rule Based Fuzzy – Neuro technique(tons)
1.	Setting load on first prop from face	9	9.01
2.		7	6.99
3.		10	9.99
4.		6	6
5.		10	10.4
6.		7	7.01
7.		8	8
8.		10	10
9.		6	5.99
10.		8	8.0

By simulation it is seen that setting load obtained from Rule Based Fuzzy Neuro (RBFN) technique is having average percentage variation 0.465 with real mine data.

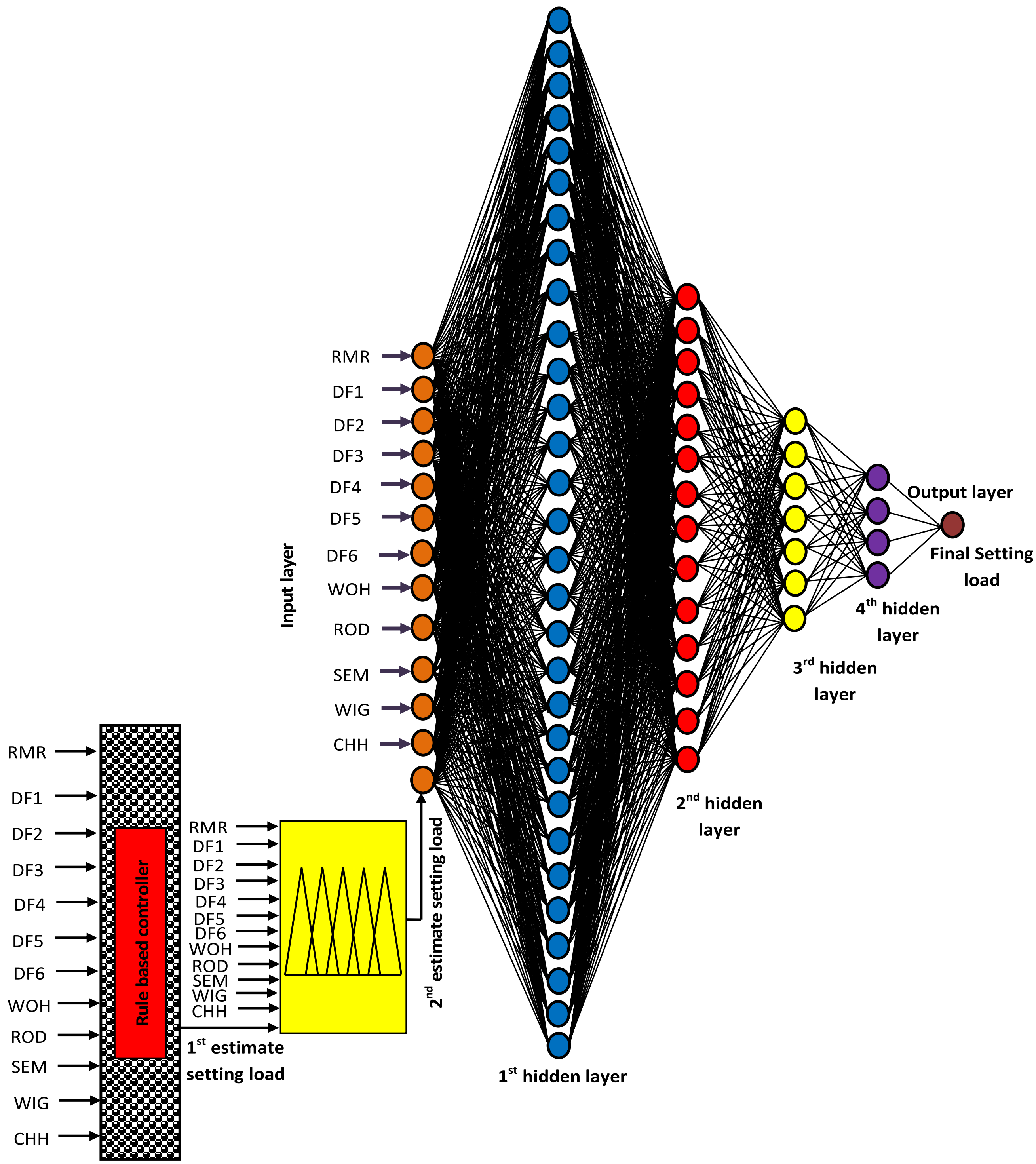


Figure 7.4 Rule based fuzzy neural controller

7.7 Results and Discussions

The above set of rules forms the core of a rule based controller. As described above the set of rules can also be combined with other techniques to yield a hybrid controller. Because the neuro-fuzzy hybrid technique has been proved to be one of the most effective among the different techniques evaluated, it will be employed in conjunction with the derived rule set to form rule based neuro-fuzzy controller and rule based fuzzy-neuro controller.

7.8 Summary

This chapter has described rule based , rule based neuro techniques, rule based fuzzy technique, rule based neuro-fuzzy and rule based fuzzy- neuro controller for the estimation of setting load on prop. The rule base technique has a set of rules obtained through rule induction and enhanced with manually derived heuristics. The enhanced set of rules is a component of the hybrid rule based neuro fuzzy and hybrid rule based fuzzy neuro technique. The demonstrations reported in this chapter have highlighted the superior performance of the rule based neuro fuzzy and rule based fuzzy –neuro technique over other techniques discussed.

CHAPTER 8

REAL DATA ANALYSIS FOR OPTIMISATION OF SUPPORT PARAMETERS

8 Real Data Analysis for Optimisation of Support Parameters

This chapter describes the analysis of real data obtained from the fields and its optimization with the help of different AI techniques and their hybridization. The results obtained from the fields were again compared with the simulated results.

8.1 Introduction

Twelve nos. of input parameters were selected which have significant effect on the setting load to be applied in the props. These input parameters are RMR, distance of the different prop from the face, seam thickness, working height, width of gallery, rock density, and charge per hole. As discussed in previous chapter 4, 5, 6 &7 the real data were simulated with different AI techniques.

8.2 Analysis of Real Data Obtained from the fields

With the help of ANN, Fuzzy Logic, Neuro-fuzzy hybrid technique, Rule based technique and its hybridization with the neural network and fuzzy logic the field data were simulated and the output received is at par with the field data.

8.3 Comparative Analysis of Real Data with Simulated Results

Real data i.e. Setting Load to be applied on prop was collected for each different set of twelve variable input parameters as shown in table 8.1. All collected input data which are non-linear in nature were simulated through different Artificial Intelligent techniques as depicted in table 8.1.

Table 8.1 Analysis of Results

Sl. No.	Input Parameters												Setting Load on Prop								
	RMR	DF1	DF2	DF3	DF4	DF5	DF6	WOH	SEM	ROD	WIG	CHH	ANN	FL	NF	FN	RB	RBN	RBF	RBFN	RBNF
1	42	0.4	1	1.6	2.2	3.0	3.6	2.8	3.6	2.4	4.2	400	9.1	9.0	9.08	9.05	9.0	9.04	9.04	9.01	9.01
2	44	0.6	1	1.8	2.2	2.6	3.4	3.0	3.4	2.2	4.2	450	8.2	8.1	8.18	8.17	8.1	8.1	8.1	8.05	8.01
3	50	0.5	0.9	1.5	2.1	2.7	3.3	3.0	3.8	2.6	4.5	600	8.1	8.2	8.17	8.10	8.1	8.12	8.11	8.02	8.05
4	50	0.4	0.8	1.2	1.8	2.4	3.0	3.6	4.0	2.2	4.2	400	8.1	8.0	8.11	8.10	8.1	8.11	8.11	8.01	8.02
5	52	0.6	1	1.6	2.2	3.0	4.0	3.8	4.2	2.2	4.2	500	7.5	7.6	7.1	7.2	7.0	7.11	7.10	7.01	7.01
6	56	0.4	1	1.8	2.2	3.0	3.6	3.4	4.8	2.8	4.0	400	7.1	7.2	7.09	7.1	7.1	7.11	7.09	7.02	7.01
7	58	0.4	1.2	1.8	2.8	3.4	3.6	3.0	3.8	2.2	4.2	450	6.5	6.3	6.0	6.1	6.1	6.2	6.3	6.0	6.0
8	50	0.4	1	1.4	2.0	2.8	3.8	2.8	4.2	2.2	4.2	400	8.1	8.0	8.11	8.10	8.1	8.11	8.09	8.0	8.01
9	50	0.4	1	1.6	2.2	2.8	3.4	4.0	4.4	2.2	4.2	450	8.7	8.5	8.4	8.3	8.4	8.3	8.4	8.50	8.55
10	48	0.4	1	1.8	2.2	2.6	3.2	4.0	3.4	24	4.2	400	9.0	9.2	9.1	9.1	91	9.4	9.3	9.0	9.0

TABLE 8.2 Real field data

Serial Nos.	Parameters	Real Data from field(Setting Load in tons)
1.	Twelve nos. input parameters	9
2.		8
3.		8
4.		8
5.		7
6.		7
7.		6
8.		8
9.		8.5
10.		9

By comparing table 8.1 and corresponding table 8.2 output parameter i.e. Setting Load applied on prop it is observed that the real results is at par with the simulated results.

8.4 Summary

In this chapter a comprehensive comparison has been done among the different simulations done through ANN, Fuzzy Logic, Neuro-Fuzzy, Fuzzy-Neuro, Rule Based technique, Rule Based Neural (RBN), Rule Based Fuzzy, Rule Based Neuro-Fuzzy and Rule Based Fuzzy-Neuro with the collected data of twelve input parameters to estimate the setting load to be applied on prop. Comparison has also been made with the real setting loads applied on the prop. It was found simulation results have good rapport with the field data. Rule Based Fuzzy- Neuro and Rule Based Neuro- Fuzzy were found the most appropriate and suitable techniques to estimate the setting load to be applied on the prop.

CHAPTER 9

RESULTS AND DISCUSSION

9 Results & Discussions

This investigation discusses the optimization of support parameters in mining terrain using Artificial Intelligent techniques. Simulating the non-linear underground mine support data by using this technique the exact setting load can be estimated which will be applied to standing support. In this chapter the performance of developed intelligent controllers are summarised and their results are outlined.

9.1 Introduction

Installation of standing support in between surface and roof rigidly is the challenging job for miners. Due care is required to be taken while installing the prop particularly near the blasting face so that it does not dislodge during blasting. Sufficient preloading is required to be applied to the prop to rigidly uphold the rock mass in the roof. In the current research Artificial Intelligent techniques have been applied to estimate the setting load to be given to the prop.

9.2 Results & Discussions

In chapter 1 & 2 introduction of the current research and literature review of the past researchers in this research areas have been presented respectively.

In chapter 3 different parameters which influence the excavation work and related safety ,have been identified in table 3.1 and analysed. All together 12 nos. of different parameters were selected for this research work. The amount of preloading to be applied on the prop is the final output. After collecting relevant data from the mine they were simulated through different AI techniques like ANN, Fuzzy, Neuro-Fuzzy, Fuzzy-Neuro, Rule Based technique, Rule Based Neural Network, Rule Base Fuzzy logic, Rule Based

Neuro-Fuzzy and Rule Based Fuzzy-Neuro techniques. Latter results were compared with the real field data and desired output was found satisfactory.

The use of Artificial Intelligent technique in mining engineering has become extremely widespread in the last few years. In this chapter 4, mine support parameters which have great influence on the underground mine support mechanism have been collected from the mines. These data were taken as input data for prediction of load on support equipments like props and rock bolts as output with the help of one of the AI technique i.e. ANN. The neural network is a multi-layer perceptron trained with backpropagation and is used for estimation of setting load to be applied in the prop in underground mines. The result obtained was at par with the field data.

In this chapter 5 twelve nos. of triangular membership functions were made for 12 nos. of input parameters and one triangular membership function for the target output i.e. setting load on prop. Fuzzy rules were drawn for most contributing decision only and after defuzzification by Mamdani criteria setting load was estimated on prop. It was found to be satisfactory.

This chapter 6 describes the optimization of mine support parameters using neuro-fuzzy and fuzzy neuro hybrid technique. The neural network is a multi-layer perceptron trained with backpropagation and is used for approximation of preloading to be applied in the prop in underground mines. The neuro-fuzzy method comprises a neural network acting as a pre-processor for a fuzzy controller. Similarily, fuzzy –neuro method comprises a fuzzy technique acting as a pre-processor for a neural controller. It has rather good performance over lone Artificial Neural Network or Fuzzy Logic.

This chapter 7 has described rule based, rule based neuro techniques, rule based fuzzy technique, rule based neuro-fuzzy and rule based fuzzy- neuro controller for the estimation of setting load on prop. In this rule based technique there has been 50 sets of situations obtained through rule induction and enhanced with manually derived heuristics. More than 10,000 such situations can be formed. These situations have been fed to See5 data mining software which yields 54 rules. 30 rules have been shown. The enhanced set of rules is a component of the hybrid rule ‑ based ‑ neuro ‑ fuzzy and hybrid rule based fuzzy –neuro technique. The demonstrations reported in this chapter have highlighted the superior performance of the rule ‑ based ‑ neuro ‑ fuzzy and rule based fuzzy –neuro technique over other techniques discussed.

In chapter 8 a comparison of all different AI techniques has been made that have been applied to estimate the setting load of prop. Rule Based Neuro-Fuzzy and Rule Based Fuzzy- Neuro have superior performance over the other developed techniques.

CHAPTER 10

CONCLUSIONS AND SCOPE FOR FUTURE WORKS

10 Conclusions and Future Works

The previous chapters have presented the background, approach and results of this research in detail. The objective of this work has been to investigate some effective techniques for estimation of setting load on the prop in underground mines. This chapter summarises the conclusions of the research and proposes idea for future work.

10.1 Introduction

In this research proposal, an attempt has been made to solve a problem related to underground mine support system to obviate the mine accidents to a great extents. Artificial Intelligent techniques have been proved to be appropriate tools to solve such type of problems

10.2 Conclusions

From the proposed investigation illustrated in this thesis the conclusion drawn are as follows:

1.In chapter 3 different influential parameters for excavation work have been identified as in table 3.1 and analysed. For this 12 nos. of different parameters were selected for this research work as input data to AI simulations. The amount of preloading to be applied on the prop is the final output. After collecting relevant data from the mine they were simulated through different AI techniques like ANN, Fuzzy, Neuro-Fuzzy, Fuzzy-Neuro, Rule Based technique, Rule Based Neural Network, Rule Base Fuzzy logic, Rule Based Neuro-Fuzzy and Rule Based Fuzzy-Neuro techniques.

The use of Artificial Intelligent technique in various activities of mining has became extremely imperative in the last few years. In this chapter 4, mine support parameters which have significant effects on the underground mine support mechanism have been collected from the mines. These data were taken as input data for prediction of load on support equipments like props and rock bolts as output with the help of one of the AI technique i.e. ANN. The neural network is a multi-layer perceptron trained with backpropagation and is used for estimation of setting load to be applied in the prop in underground mines. The sigmoidal transfer function was used for simulation in easiest way. The results were correlated with the field data and found satisfactory.

In chapter 5, fields data were simulated with fuzzy logic technique. Twelve nos. of Mamdani fuzzy model having 5 triangular membership functions for each were made for 12 nos. of input parameters and one triangular membership function for the target output i.e. setting load on prop. Fuzzy rules were drawn for most contributing decision only and after defuzzification by Mamdani Centroid of Area criteria setting load was estimated on prop. The results obtained using fuzzy logic for setting the prop load are in agreement with the real field data.

Chapter 6 explains the optimization of mine support parameters using neuro-fuzzy and fuzzy- neuro hybrid technique. The neural network is a multi-layer perceptron trained with backpropagation and is used for approximation of preloading to be applied in the prop in underground mines. The neuro-fuzzy method comprises a neural network acting as a pre-processor for a fuzzy controller. Similarly, fuzzy–neuro method comprises a fuzzy model acting as a pre-processor for a neural controller. It has rather good performance over lone Artificial Neural Network or Fuzzy Logic.

This chapter 7 depicted the Rule Based, Rule Based Neuro techniques, Rule Based Fuzzy technique, Rule Based Neuro-Fuzzy and Rule Based Fuzzy-Neuro controller for the estimation of setting load on prop. In this Rule Based technique there has been 50 sets of situations obtained through rule induction and enhanced with manually derived heuristics. More than 10,000 such situations can be formed. These situation have been fed to See5 data mining software which yields 54 rules. 30 rules have been shown. The enhanced set of rules is a component of the hybrid rule based neuro ‐ fuzzy and hybrid rule based fuzzy –neuro technique. The demonstrations reported in this chapter have highlighted the superior performance of the rule based neuro ‐ fuzzy and rule based fuzzy –neuro technique over other techniques discussed.

A comparison has been made in chapter 8 for all different AI techniques which have been applied to estimate the setting load of prop. Rule Based Neuro- Fuzzy and Rule Based Fuzzy- Neuro have superior performance over the other techniques.

10.3 Future Works

This research work provides a foundation for future expansion of integrated designing approaches of intelligent controller based on artificial intelligence technique. Regardless of all research that has been conducted, underground mine support system is still an open area of research. There are a number of interesting directions to pursue as future research work. The suggestions with several crucial and promising researches for future investigation are as follows.

In the current research work, techniques have been developed for estimation of setting load on prop for avoidance of mine accidents. However, further development of these techniques may be required in installation of other active support like rock bolting, roof stitching, and cable bolting etc. to enhance safety in mines. This will make the algorithm more effective in dealing with unpredictable real life situations. The other AI techniques apart from that have been applied in the current research work and may be explored for the most appropriate suitability in mine support system. Further modifications in these optimization techniques may be carried out to increase safety in mining excavations. These AI techniques may be applied in other mining excavation activities like subsidence, ventilation, rock characterization etc. in underground mines.

APPENDIX - A

Data for Rule - Based Controller

The data set used in the algorithm to generate the rules:

Each data set comprises of Rock Mass Rating (RMR), distance of first prop from the face(DF1), distance of second prop from the face(DF2), distance of third prop from the face(DF3), distance of fourth prop from the face (DF4), distance of fifth prop from the face (DF5), distance of sixth prop from the face (DF6), working height (WOH), rock density (ROD), seam thickness (SEM), width of gallery (WIG), charge per hole (CHH) and setting load on prop(SLP).

RMR	DF1	DF2	DF3	DF4	DF5	DF6	WOH	ROD	SEM	WIG	CHH	SLP
38,	0.4,	1.0,	2.1,	1.6,	2.4,	2.6,	2.8,	2.3,	3.6,	4.0,	400,	8
40,	0.5,	0.9,	1.2,	1.7,	2.5,	2.4,	2.7,	2.2,	3.4,	4.1,	490,	7
39,	0.6,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	4.8,	4.2,	580,	6
38,	0.4,	0.8,	1.9,	1.9,	2.3,	3.5,	2.7,	2.2,	3.9,	4.5,	455,	5
40,	0.5,	0.9,	1.2,	2.9,	2.4,	2.8,	2.9,	2.5,	3.7,	4.1,	450,	9
39,	0.7,	1.2,	2.0,	2.2,	3.1,	3.2,	2.5,	2.4,	4.5,	4.3,	430,	7
40,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.1,	460,	9
42,	0.7,	1.3,	1.9,	2.3,	3.2,	2.6,	3.8,	2.6,	3.7,	4.2,	500,	8
39,	0.6,	0.9,	1.6,	1.7,	2.1,	2.5,	2.6,	2.3,	3.6,	4.3,	400,	6
45,	0.4,	1.0,	1.5,	2.4,	2.4,	3.0,	2.5,	2.7,	3.4,	4.2,	450,	9
55,	0.7,	0.8,	1.3,	1.8,	3.6,	3.3,	2.4,	2.9,	4.5,	4.4,	560,	5
44,	0.4,	0.9,	2.0,	2.8,	3.4,	4.2,	3.5,	2.3,	3.6,	4.2,	500,	7
46,	0.6,	1.1,	2.1,	2.2,	2.9,	2.5,	3.6,	2.2,	3.7,	4.0,	488,	6
42,	0.7,	0.8,	1.2,	2.9,	2.3,	2.7,	2.5,	2.6,	3.5,	4.3,	460,	5
38,	0.5,	1.2,	1.3,	1.9,	2.1,	2.5,	2.7,	2.3,	3.4,	4.1,	430,	8

53, 0.6, 0.9, 2.1, 2.2, 2.8, 3.1, 3.3, 2.9, 4.2, 4.4, 459, 6

51, 0.7, 0.8, 2.2, 1.7, 3.6, 3.2, 2.8, 2.3, 3.5, 4.3, 400, 5

40, 0.5, 0.9, 1.5, 2.5, 2.2, 4.4, 3.8, 2.4, 4.2, 4.1, 440, 7

39, 0.4, 1.1, 2.1, 2.6, 3.5 3.3, 2.5, 2.9, 4.4, 4.2, 450, 8

55, 0.8, 1.2, 1.3, 2.2, 2.1, 2.5, 3.1, 2.8, 3.5, 4.4, 400, 5

38, 0.5, 0.9, 1.2, 1.7, 2.5, 2.4, 2.7, 2.2, 3.4, 4.1, 540, 7

39, 0.6, 0.7, 2.0, 1.8, 2.2, 2.5, 2.6, 2.3, 3.8, 4.2, 460, 6

38, 0.4, 0.8, 1.9, 1.9, 2.3, 3.5, 2.7, 2.2, 3.9, 4.5, 550, 5

43, 0.5, 0.9, 1.2, 2.9, 2.4, 2.8, 2.9, 2.5, 3.7, 4.1, 450, 8

45, 0.4, 1.0, 1.5, 2.4, 2.4, 3.0, 3.5, 2.7, 3.4, 4.2, 470, 9

55, 0.7, 0.8, 1.3, 1.8, 3.6, 3.3, 2.4, 2.9, 3.5, 4.4, 560, 5

44, 0.4, 0.9, 2.0, 2.8, 3.4, 4.2, 3.5, 2.3, 3.6, 4.2, 500, 7

46, 0.5, 1.1, 2.1, 2.2, 2.9, 2.5, 3.6, 2.2, 3.7, 4.0, 480, 6

42, 0.6, 0.9, 1.2, 2.9, 2.3, 2.7, 2.5, 2.6, 3.5, 4.3, 460, 5

48, 0.5, 1.2, 1.3, 1.9, 2.1, 2.5, 2.7, 2.3, 3.4, 4.1, 430, 8

56, 0.6, 0.8, 1.3, 1.8, 3.6, 3.2, 2.4, 2.9, 3.5, 4.4, 560, 5

44, 0.4, 0.9, 2.0, 2.8, 3.4, 4.2, 3.5, 2.3, 3.6, 4.2, 500, 7

39, 0.6, 1.3, 2.1, 2.2, 2.9, 2.5, 3.6, 2.2, 3.7, 4.0, 580, 6

42, 0.7, 0.8, 1.2, 2.8, 2.3, 2.7, 4.2, 2.6, 3.5, 4.3, 460, 5

48, 0.5, 1.2, 1.3, 1.9, 2.1, 2.5, 2.7, 2.3, 3.4, 4.1, 430, 8

57, 0.6, 0.9, 2.1, 2.2, 2.8, 3.1, 3.3, 2.9, 4.2, 4.4, 459, 6

51, 0.7, 0.8, 2.2, 1.7, 3.5, 3.2, 2.8, 2.3, 3.5, 4.3, 410, 5

40, 0.5, 0.9, 1.5, 2.5, 2.2, 4.4, 3.8, 2.4, 4.2, 4.1, 540, 7

39, 0.4, 1.1, 2.1, 2.6, 3.5 3.3, 2.5, 2.9, 4.4, 4.2, 450, 8

56, 0.6, 1.2, 1.3, 2.2, 2.1, 2.5, 3.1, 2.8, 3.5, 4.4, 430, 5

38, 0.5, 0.9, 1.2, 1.7, 3.4, 2.4, 2.8, 2.2, 3.4, 4.1, 490, 7

39, 0.7, 0.7, 2.0, 1.8, 2.2, 2.5, 2.6, 2.3, 3.8, 4.2, 460, 6

48, 0.4, 1.3, 1.9, 1.9, 2.3, 3.5, 3.7, 2.2, 3.9, 4.5, 530, 5

38, 0.5, 1.2, 1.3, 2.6, 3.1, 2.5, 2.5, 2.3, 4.4, 4.1, 430, 8

53, 0.6, 0.9, 2.1, 2.8, 2.5, 3.1, 3.3, 2.9, 4.2, 4.4, 450, 6

51, 0.6, 0.8, 2.2, 1.7, 3.6, 3.2, 2.8, 2.3, 3.5, 4.3, 400, 5

40, 0.5, 0.9, 1.5, 2.5, 2.2, 4.4, 3.8, 2.4, 4.2, 4.1, 540, 7

39, 0.4, 1.1, 2.1, 2.6, 3.5 3.3, 2.5, 2.9, 4.4, 4.2, 450, 8

35, 0.5, 1.2, 1.3, 1.9, 2.1, 2.5, 2.6, 2.3, 3.4, 4.1, 430, 8

49, 0.6, 0.9, 2.1, 2.2, 2.8, 3.1, 3.3, 2.9, 4.2, 4.4, 440, 6

55, 0.7, 0.8, 2.2, 1.6, 3.6, 2.2, 2.7, 2.3, 3.5, 4.3, 510, 5

40, 0.5, 0.9, 1.5, 2.5, 2.2, 4.3, 3.8, 2.4, 4.2, 4.1, 440, 7

39, 0.4, 1.1, 2.1, 2.6, 3.5 3.3, 2.5, 2.9, 4.4, 4.2, 450, 8

55, 0.8, 1.2, 1.3, 2.2, 2.1, 2.5, 3.1, 2.8, 3.5, 4.4, 400, 5

39, 0.6, 0.7, 2.0, 1.8, 2.2, 2.5, 2.6, 2.3, 3.8, 4.2, 590, 6

48, 0.4, 0.8, 1.6, 1.9, 2.3, 3.5, 2.7, 2.2, 3.9, 4.5, 430, 5

43, 0.5, 0.9, 1.2, 2.9, 2.4, 2.8, 2.9, 2.5, 3.7, 4.1, 450, 8

45, 0.4, 1.0, 1.5, 2.4, 2.4, 3.0, 3.5, 2.7, 3.4, 4.2, 450, 9

55, 0.7, 0.8, 1.3, 1.8, 3.6, 3.3, 2.4, 2.9, 3.5, 4.4, 460, 5

44, 0.4, 0.9, 2.0, 2.8, 3.4, 4.2, 3.5, 2.3, 3.6, 4.2, 500, 7

46, 0.5, 1.1, 2.1, 2.2, 2.9, 2.5, 3.6, 2.2, 3.7, 4.0, 580, 6

52, 0.6, 0.9, 1.2, 2.9, 2.3, 2.7, 2.5, 2.6, 3.5, 4.3, 460, 5

48, 0.5, 1.2, 1.4, 1.9, 2.1, 2.5, 2.7, 2.3, 3.4, 4.1, 430, 8

56, 0.6, 0.8, 1.3, 1.8, 3.6, 3.2, 2.4, 2.9, 3.5, 4.4, 560, 5

47, 0.4, 0.9, 2.0, 2.8, 3.4, 4.2, 3.5, 2.3, 3.6, 4.2, 500, 7

39,	0.6,	1.3,	2.1,	2.2,	2.9,	2.5,	3.6,	2.2,	3.7,	4.0,	480,	6
42,	0.7,	0.8,	1.2,	2.8,	2.3,	2.7,	4.2,	2.6,	3.5,	4.3,	460,	5
48,	0.5,	1.2,	1.3,	1.9,	2.1,	2.5,	2.7,	2.3,	3.4,	4.1,	430,	8
57,	0.6,	0.9,	2.1,	2.2,	2.8,	3.1,	3.3,	2.9,	4.2,	4.4,	459,	6
53,	0.7,	0.8,	2.2,	1.7,	3.5,	3.2,	2.8,	2.3,	3.5,	4.3,	400,	5
43,	0.5,	0.9,	1.5,	2.5,	2.2,	4.4,	3.8,	2.4,	4.2,	4.1,	540,	7
39,	0.4,	1.1,	2.1,	2.6,	3.5	3.3,	2.5,	2.9,	4.4,	4.2,	450,	8
56,	0.6,	1.2,	1.3,	2.2,	2.1,	2.5,	3.1,	2.8,	3.5,	4.4,	430,	5
38,	0.5,	0.9,	1.2,	1.7,	3.4,	2.4,	2.8,	2.2,	3.4,	4.1,	560,	7
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	510,	6
48,	0.4,	1.3,	1.9,	1.9,	2.3,	3.5,	3.7,	2.2,	3.9,	4.5,	430,	5
38,	0.5,	1.2,	1.3,	2.6,	3.1,	2.5,	2.5,	2.3,	4.4,	4.1,	430,	8
56,	0.6,	0.9,	2.1,	2.8,	2.5,	3.1,	3.3,	2.9,	4.2,	4.4,	450,	6
39,	0.6,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	4.8,	4.2,	410,	6
48,	0.4,	0.8,	1.9,	1.9,	2.3,	3.5,	2.7,	2.2,	3.9,	4.5,	550,	5
45,	0.5,	0.9,	1.2,	2.9,	2.4,	2.8,	2.9,	2.5,	3.7,	4.1,	450,	9
39,	0.7,	1.2,	2.0,	2.2,	3.1,	3.2,	2.5,	2.4,	4.5,	4.3,	430,	7
40,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.1,	460,	9
42,	0.7,	1.3,	1.9,	2.3,	3.2,	2.6,	3.8,	2.6,	3.7,	4.2,	500,	8
39,	0.6,	0.9,	1.6,	1.7,	2.1,	2.5,	2.6,	2.3,	3.6,	4.3,	400,	6
45,	0.4,	1.0,	1.5,	2.4,	2.4,	3.0,	2.5,	2.7,	3.4,	4.2,	450,	9
42,	0.7,	0.8,	1.2,	2.9,	2.3,	2.7,	2.5,	2.6,	3.5,	4.3,	460,	5
38,	0.5,	1.2,	1.3,	1.9,	2.1,	2.5,	2.7,	2.3,	3.4,	4.1,	430,	8
53,	0.6,	0.9,	2.1,	2.2,	2.8,	3.1,	3.3,	2.9,	4.2,	4.4,	459,	6
40,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.1,	460,	9

51, 0.7, 0.8, 2.2, 1.7, 3.6, 3.2, 2.8, 2.3, 3.5, 4.3, 410, 5

40, 0.5, 0.9, 1.5, 2.5, 2.2, 4.4, 3.8, 2.4, 4.2, 4.1, 440, 7

39, 0.4, 1.1, 2.1, 2.6, 3.5 3.3, 2.5, 2.9, 4.4, 4.2, 450, 8

55, 0.8, 1.2, 1.3, 2.2, 2.1, 2.5, 3.1, 2.8, 3.5, 4.4, 400, 5

38, 0.5, 0.9, 1.2, 1.7, 2.5, 2.4, 2.7, 2.2, 3.4, 4.1, 570, 7

42, 0.7, 0.8, 1.3, 2.8, 2.3, 2.7, 4.2, 2.6, 3.5, 4.3, 460, 5

45, 0.5, 1.2, 1.9, 2.5, 2.1, 2.5, 2.7, 2.3, 3.4, 4.1, 430, 8

57, 0.6, 0.9, 2.1, 2.2, 2.8, 3.1, 3.3, 2.9, 4.2, 4.4, 459, 6

51, 0.7, 0.8, 2.2, 1.7, 3.5, 3.2, 2.8, 2.3, 3.5, 4.3, 400, 5

40, 0.5, 1.1, 1.8, 2.5, 3.1, 2.9, 2.6, 2.9, 3.6, 4.1, 460, 9

39, 0.7, 0.7, 2.0, 1.8, 2.2, 2.5, 2.6, 2.3, 3.8, 4.2, 520, 6

48, 0.4, 1.1, 1.9, 1.9, 2.3, 3.5, 3.7, 2.2, 3.9, 4.5, 430, 5

42, 0.6, 1.0, 1.5, 2.4, 2.4, 3.0, 2.4, 2.7, 3.4, 4.2, 450, 9

39, 0.7, 0.8, 1.2, 2.9, 2.3, 2.7, 2.5, 2.6, 3.5, 4.3, 560, 5

38, 0.5, 1.2, 1.3, 1.9, 2.1, 2.5, 2.7, 2.3, 3.4, 4.1, 430, 8

55, 0.6, 0.9, 2.1, 2.2, 2.8, 3.1, 3.3, 2.9, 4.2, 4.4, 459, 6

42, 0.5, 1.2, 1.5, 2.5, 2.2, 4.4, 3.8, 2.4, 4.2, 4.1, 540, 7

38, 0.4, 0.9, 1.2, 1.7, 3.4, 2.4, 2.8, 2.2, 3.4, 4.4, 590, 5

39, 0.7, 0.7, 2.0, 1.8, 2.2, 2.5, 2.6, 2.3, 3.8, 4.2, 500, 6

42, 0.5, 0.8, 1.2, 2.8, 2.3, 2.7, 4.2, 2.6, 3.5, 4.3, 460, 7

45, 0.4, 1.2, 1.3, 1.9, 2.1, 2.5, 2.7, 2.3, 3.4, 4.1, 430, 8

40, 0.5, 1.1, 1.8, 2.5, 3.1, 2.9, 2.6, 2.9, 3.6, 4.2, 460, 9

39, 0.7, 0.8, 1.2, 2.9, 2.3, 2.7, 2.5, 2.6, 3.5, 4.3, 560, 5

38, 0.5, 1.2, 1.3, 1.9, 2.1, 2.5, 2.7, 2.3, 3.4, 4.1, 430, 8

42, 0.7, 0.8, 1.2, 2.8, 2.3, 2.7, 4.2, 2.6, 3.5, 4.3, 460, 5

48,	0.5,	1.2,	1.3,	1.9,	2.1,	2.5,	2.7,	2.3,	3.4,	4.1,	430,	8
57,	0.6,	0.9,	2.1,	2.2,	2.8,	3.1,	3.3,	2.9,	4.2,	4.4,	459,	6
53,	0.7,	0.8,	2.2,	1.7,	3.5,	3.2,	2.8,	2.3,	3.5,	4.3,	400,	5
43,	0.5,	0.9,	1.5,	2.5,	2.2,	4.4,	3.8,	2.4,	4.2,	4.1,	540,	7
39,	0.4,	1.1,	2.1,	2.6,	3.5	3.3,	2.5,	2.9,	4.4,	4.2,	450,	8
56,	0.6,	1.2,	1.3,	2.2,	2.1,	2.5,	3.1,	2.8,	3.5,	4.4,	430,	5
57,	0.6,	0.9,	2.1,	2.2,	2.8,	3.1,	3.3,	2.9,	4.2,	4.4,	459,	6
51,	0.7,	0.8,	2.2,	1.7,	3.5,	3.2,	2.8,	2.3,	3.5,	4.3,	400,	5
40,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.1,	460,	9
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	520,	6
48,	0.4,	1.1,	1.9,	1.9,	2.3,	3.5,	3.7,	2.2,	3.9,	4.5,	430,	5
38,	0.4,	1.0,	2.1,	1.6,	2.4,	2.6,	2.8,	2.3,	3.6,	4.0,	400,	8
40,	0.5,	0.9,	1.2,	1.7,	2.5,	2.4,	2.7,	2.2,	3.4,	4.1,	490,	7
39,	0.6,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	4.8,	4.2,	580,	6
38,	0.4,	0.8,	1.9,	1.9,	2.3,	3.5,	2.7,	2.2,	3.9,	4.5,	455,	5
40,	0.5,	0.9,	1.2,	2.9,	2.4,	2.8,	2.9,	2.5,	3.7,	4.1,	450,	9
39,	0.7,	1.2,	2.0,	2.2,	3.1,	3.2,	2.5,	2.4,	4.5,	4.3,	430,	7
40,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.1,	460,	9
42,	0.7,	1.3,	1.9,	2.3,	3.2,	2.6,	3.8,	2.6,	3.7,	4.2,	500,	8
39,	0.4,	1.1,	2.1,	2.6,	3.5	3.3,	2.5,	2.9,	4.4,	4.2,	450,	8
56,	0.6,	1.2,	1.3,	2.2,	2.1,	2.5,	3.1,	2.8,	3.5,	4.4,	430,	5
38,	0.5,	0.9,	1.2,	1.7,	3.4,	2.4,	2.8,	2.2,	3.4,	4.1,	560,	7
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	510,	6
48,	0.4,	1.3,	1.9,	1.7,	2.3,	3.5,	3.7,	2.2,	3.9,	4.5,	430,	5
38,	0.5,	1.2,	1.3,	2.6,	3.1,	2.5,	2.5,	2.3,	4.4,	4.1,	430,	8

56, 0.6, 0.9, 2.1, 2.8, 2.5, 3.1, 3.3, 2.9, 4.2, 4.4, 450, 6

39, 0.7, 0.8, 1.2, 2.9, 2.3, 2.7, 2.5, 2.6, 3.5, 4.3, 560, 5

38, 0.5, 1.2, 1.3, 1.9, 2.1, 2.5, 2.7, 2.3, 3.4, 4.1, 430, 8

42, 0.7, 0.8, 1.2, 2.8, 2.3, 2.7, 4.2, 2.6, 3.5, 4.3, 460, 5

48, 0.5, 1.2, 1.3, 1.9, 2.1, 2.5, 2.7, 2.3, 3.4, 4.1, 430, 8

57, 0.6, 0.9, 2.1, 2.2, 2.8, 3.1, 3.3, 2.9, 4.2, 4.4, 459, 6

53, 0.7, 0.8, 2.2, 1.7, 3.5, 3.2, 2.8, 2.3, 3.5, 4.3, 400, 5

43, 0.5, 0.9, 1.5, 2.5, 2.2, 4.4, 3.8, 2.4, 4.2, 4.1, 540, 7

55, 0.6, 0.9, 2.1, 2.2, 2.8, 3.1, 3.3, 2.9, 4.2, 4.4, 459, 6

42, 0.5, 1.2, 1.5, 2.5, 2.2, 4.4, 3.8, 2.4, 4.2, 4.1, 540, 7

38, 0.4, 0.9, 1.2, 1.7, 3.4, 2.4, 2.8, 2.2, 3.4, 4.4, 590, 5

39, 0.7, 0.7, 2.0, 1.8, 2.2, 2.5, 2.6, 2.3, 3.8, 4.2, 500, 6

42, 0.5, 0.8, 1.2, 2.8, 2.3, 2.7, 4.2, 2.6, 3.5, 4.3, 460, 7

45, 0.4, 1.2, 1.3, 1.9, 2.1, 2.5, 2.7, 2.3, 3.4, 4.1, 430, 8

40, 0.5, 1.1, 1.8, 2.5, 3.1, 2.9, 2.6, 2.9, 3.6, 4.1, 460, 9

39, 0.7, 0.8, 1.2, 2.9, 2.3, 2.7, 2.5, 2.6, 3.5, 4.3, 560, 5

38, 0.5, 1.2, 1.3, 1.9, 2.1, 2.5, 2.7, 2.3, 3.4, 4.1, 430, 8

39, 0.6, 0.7, 2.0, 1.8, 2.2, 2.5, 2.6, 2.3, 4.8, 4.2, 410, 6

48, 0.4, 0.8, 1.9, 1.9, 2.3, 3.5, 2.7, 2.2, 3.9, 4.5, 550, 5

45, 0.5, 0.9, 1.2, 2.9, 2.4, 2.8, 2.9, 2.5, 3.7, 4.1, 450, 9

39, 0.7, 1.2, 2.0, 2.2, 3.1, 3.2, 2.5, 2.4, 4.5, 4.3, 430, 7

40, 0.5, 1.1, 1.8, 2.5, 3.1, 2.9, 2.6, 2.9, 3.6, 4.1, 460, 9

42, 0.7, 1.3, 1.9, 2.3, 3.2, 2.6, 3.8, 2.6, 3.7, 4.2, 500, 8

38, 0.6, 0.9, 1.6, 1.7, 2.1, 2.5, 2.6, 2.3, 3.6, 4.3, 400, 6

39, 0.7, 0.8, 1.2, 2.9, 2.3, 2.7, 2.5, 2.6, 3.5, 4.3, 560, 5

48,	0.5,	1.2,	1.3,	1.9,	2.1,	2.5,	2.7,	2.3,	3.4,	4.1,	430,	8
55,	0.6,	0.9,	2.1,	2.2,	2.8,	3.1,	3.3,	2.9,	4.2,	4.4,	459,	6
42,	0.5,	1.2,	1.5,	2.5,	2.2,	4.4,	3.8,	2.4,	4.2,	4.1,	540,	7
38,	0.4,	0.9,	1.2,	1.7,	3.4,	2.4,	2.8,	2.2,	3.4,	4.4,	590,	5
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	500,	6
42,	0.5,	0.8,	1.2,	2.8,	2.3,	2.7,	4.2,	2.6,	3.5,	4.3,	460,	7
45,	0.4,	1.2,	1.3,	1.9,	2.1,	2.5,	2.7,	2.3,	3.4,	4.1,	430,	8
40,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.3,	460,	9
39,	0.4,	0.8,	2.1,	2.6,	3.5	3.3,	2.5,	2.9,	4.4,	4.2,	450,	8
55,	0.8,	1.2,	1.3,	2.2,	2.1,	2.5,	3.1,	2.8,	3.5,	4.4,	400,	5
38,	0.5,	0.9,	1.2,	1.7,	2.5,	2.4,	2.7,	2.2,	3.4,	4.1,	570,	7
42,	0.7,	0.8,	1.2,	2.8,	2.3,	2.7,	4.2,	2.6,	3.5,	4.3,	460,	5
45,	0.5,	1.2,	1.3,	1.9,	2.1,	2.5,	2.7,	2.3,	3.4,	4.1,	430,	8
57,	0.6,	0.9,	2.1,	2.2,	2.8,	3.1,	3.3,	2.9,	4.2,	4.4,	459,	6
51,	0.7,	0.8,	2.2,	1.7,	3.5,	3.2,	2.8,	2.3,	3.5,	4.3,	400,	5
40,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.1,	460,	9
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	520,	6
42,	0.5,	1.2,	1.5,	2.5,	2.2,	4.4,	3.8,	2.4,	4.2,	4.1,	540,	7
38,	0.4,	0.9,	1.2,	1.7,	3.4,	2.4,	2.8,	2.2,	3.4,	4.4,	590,	5
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	500,	6
42,	0.5,	0.8,	1.2,	2.8,	2.3,	2.7,	4.2,	2.6,	3.5,	4.3,	460,	7
45,	0.4,	1.2,	1.3,	1.9,	2.1,	2.5,	2.7,	2.3,	3.4,	4.1,	430,	8
40,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.3,	460,	9
43,	0.7,	0.9,	1.5,	2.5,	2.2,	4.4,	3.8,	2.4,	4.2,	4.1,	540,	7
39,	0.4,	1.1,	2.1,	2.6,	3.5	3.3,	2.5,	2.9,	4.4,	4.2,	450,	8

56, 0.6, 1.2, 1.3, 2.2, 2.1, 2.5, 3.1, 2.8, 3.5, 4.4, 430, 5

57, 0.5, 0.9, 2.1, 2.2, 2.8, 3.1, 3.3, 2.9, 4.2, 4.1, 459, 6

51, 0.7, 0.8, 2.2, 1.7, 3.5, 3.2, 2.8, 2.3, 3.5, 4.3, 400, 5

40, 0.5, 1.1, 1.8, 2.5, 3.1, 2.9, 2.6, 2.9, 3.6, 4.1, 460, 9

39, 0.7, 0.7, 2.0, 1.8, 2.2, 2.5, 2.6, 2.3, 3.8, 4.2, 520, 6

48, 0.4, 1.1, 1.9, 1.9, 2.3, 3.5, 3.7, 2.2, 3.9, 4.5, 430, 5

39, 0.7, 1.2, 2.0, 2.2, 3.1, 3.2, 2.5, 2.4, 4.5, 4.3, 430, 7

40, 0.5, 1.1, 1.8, 2.5, 3.3, 2.9, 2.6, 2.9, 3.6, 4.1, 460, 9

42, 0.7, 1.3, 1.9, 2.3, 3.2, 2.6, 3.8, 2.6, 3.7, 4.2, 500, 8

38, 0.6, 0.9, 1.6, 1.7, 2.1, 2.5, 2.6, 2.3, 3.6, 4.3, 400, 6

39, 0.7, 0.8, 1.2, 2.9, 2.3, 2.7, 2.5, 2.6, 3.5, 4.2, 560, 5

48, 0.5, 1.2, 1.3, 1.9, 2.1, 2.5, 2.7, 2.3, 3.4, 4.1, 430, 8

55, 0.6, 0.9, 2.1, 2.2, 2.8, 3.1, 3.3, 2.9, 4.2, 4.4, 459, 6

42, 0.5, 1.2, 1.5, 2.5, 2.2, 4.4, 3.8, 2.4, 4.5, 4.1, 540, 7

38, 0.4, 0.9, 1.2, 1.7, 3.4, 2.4, 2.8, 2.2, 3.4, 4.4, 590, 5

53, 0.7, 0.8, 2.2, 1.8, 3.5, 3.2, 2.8, 2.3, 3.5, 4.3, 400, 5

43, 0.5, 0.9, 1.5, 2.5, 2.2, 4.4, 3.8, 2.4, 4.2, 4.1, 540, 7

39, 0.4, 1.1, 2.1, 2.6, 3.5 3.3, 2.5, 2.9, 4.4, 4.2, 450, 8

56, 0.6, 1.2, 1.3, 2.2, 2.1, 2.5, 3.1, 2.8, 3.5, 4.3, 430, 5

57, 0.5, 0.9, 2.1, 2.5 , 2.8, 3.1, 3.3, 2.9, 4.2, 4.4, 459, 6

51, 0.7, 0.8, 2.2, 1.7, 3.5, 3.2, 2.8, 2.3, 3.5, 4.3, 400, 5

40, 0.5, 1.1, 1.8, 2.5, 3.1, 2.9, 2.6, 2.9, 3.6, 4.1, 460, 9

39, 0.7, 0.7, 2.0, 1.8, 2.2, 2.5, 2.6, 2.3, 3.8, 4.2, 520, 6

40, 0.6, 1.3, 2.1, 2.2, 2.9, 2.4, 3.6, 2.2, 3.7, 4.0, 580, 8

42, 0.7, 0.8, 1.2, 2.8, 2.3, 2.7, 4.2, 2.6, 3.5, 4.3, 460, 5

48,	0.5,	1.2,	1.3,	1.9,	2.1,	2.5,	2.7,	2.3,	3.4,	4.1,	430,	8
57,	0.6,	0.9,	2.1,	2.2,	2.8,	3.1,	3.3,	2.9,	4.2,	4.4,	459,	6
51,	0.7,	0.8,	2.2,	1.7,	3.5,	3.2,	2.8,	2.3,	3.5,	4.3,	410,	5
40,	0.5,	0.9,	1.5,	2.5,	2.2,	4.4,	3.8,	2.4,	4.2,	4.1,	540,	7
39,	0.4,	1.1,	2.1,	2.6,	3.5	3.3,	2.5,	2.9,	4.4,	4.2,	450,	8
40,	0.5,	1.3,	1.8,	2.5,	3.1,	2.9,	2.6,	2.5,	3.6,	4.1,	460,	9
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.8,	2.3,	3.8,	4.2,	520,	6
42,	0.5,	1.2,	1.5,	2.5,	2.6,	4.4,	3.8,	2.4,	4.2,	4.1,	540,	7
38,	0.4,	0.9,	1.2,	1.7,	3.4,	2.4,	2.8,	2.2,	3.4,	4.4,	590,	5
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	500,	6
45,	0.4,	1.2,	2.1,	2.2,	3.1,	3.2,	2.5,	2.4,	4.5,	4.3,	430,	7
40,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.1,	460,	9
42,	0.7,	1.3,	1.9,	2.3,	3.2,	2.6,	3.8,	2.6,	3.7,	4.2,	500,	8
39,	0.6,	0.9,	1.6,	1.7,	2.1,	2.5,	2.6,	2.3,	3.6,	4.3,	400,	6
45,	0.4,	1.0,	1.5,	2.4,	2.4,	3.0,	2.5,	2.7,	3.4,	4.2,	450,	9
55,	0.7,	0.8,	1.3,	1.8,	3.6,	3.3,	2.4,	2.9,	4.5,	4.4,	560,	5
44,	0.4,	0.9,	2.0,	2.8,	3.4,	4.2,	3.5,	2.3,	3.6,	4.2,	500,	7
46,	0.6,	1.1,	2.1,	2.2,	2.9,	2.5,	3.6,	2.2,	3.7,	4.0,	488,	6
42,	0.7,	0.8,	1.2,	2.9,	2.3,	2.7,	2.5,	2.6,	3.5,	4.3,	460,	5
38,	0.5,	1.2,	1.3,	1.9,	2.1,	2.5,	2.7,	2.3,	3.4,	4.1,	430,	8
53,	0.6,	0.9,	2.1,	2.2,	2.8,	3.1,	3.3,	2.9,	4.2,	4.4,	459,	6
51,	0.7,	0.8,	2.2,	1.7,	3.6,	3.2,	2.8,	2.3,	3.5,	4.3,	400,	5
38,	0.6,	0.9,	1.6,	2.7,	2.1,	2.5,	2.6,	2.3,	3.6,	4.2,	400,	6
39,	0.7,	0.8,	1.2,	2.9,	2.3,	2.7,	2.5,	2.6,	3.5,	4.3,	560,	5
48,	0.5,	1.2,	1.3,	1.9,	2.1,	2.5,	2.7,	2.3,	3.4,	4.1,	430,	8

55, 0.6, 0.9, 2.1, 2.2, 2.8, 3.1, 3.3, 2.9, 4.2, 4.4, 459, 6

42, 0.5, 1.2, 1.5, 2.5, 2.2, 4.4, 3.8, 2.4, 3.5, 4.1, 540, 7

38, 0.4, 0.9, 1.2, 1.7, 3.4, 2.4, 2.8, 2.2, 3.4, 4.4, 590, 5

53, 0.7, 1.3, 2.2, 1.8, 3.5, 3.2, 2.8, 2.3, 3.5, 4.3, 400, 8

43, 0.5, 0.9, 1.5, 2.5, 2.2, 4.4, 3.8, 2.4, 4.2, 4.1, 540, 7

39, 0.4, 1.1, 2.1, 2.6, 3.5 3.3, 2.5, 2.9, 4.4, 4.2, 450, 8

40, 0.5, 1.2, 1.8, 2.5, 3.1, 2.9, 2.6, 2.9, 3.6, 4.1, 460, 9

39, 0.7, 0.7, 2.0, 1.8, 2.2, 2.5, 2.6, 2.3, 3.8, 4.2, 520, 6

42, 0.5, 1.2, 1.5, 2.5, 2.9, 4.4, 3.8, 2.4, 4.2, 4.1, 540, 7

38, 0.4, 0.9, 1.2, 1.7, 3.4, 2.4, 2.8, 2.2, 3.4, 4.4, 590, 5

39, 0.7, 0.7, 2.0, 1.8, 2.2, 2.5, 2.6, 2.3, 3.8, 4.2, 520, 6

42, 0.5, 1.2, 1.5, 2.5, 2.2, 4.4, 3.8, 2.4, 4.2, 4.1, 540, 7

38, 0.4, 0.9, 1.2, 1.7, 3.4, 2.4, 2.8, 2.2, 3.4, 4.4, 590, 5

39, 0.7, 1.1, 2.1, 2.6, 3.5 3.3, 2.5, 2.9, 4.4, 4.2, 450, 8

56, 0.6, 1.2, 1.3, 2.2, 2.1, 2.5, 3.1, 2.8, 3.5, 4.4, 430, 5

44, 0.4, 0.9, 2.0, 2.8, 3.4, 4.2, 3.5, 2.3, 3.6, 4.2, 500, 7

46, 0.5, 1.1, 2.1, 2.2, 2.9, 2.5, 3.6, 2.2, 3.7, 4.0, 580, 6

52, 0.6, 0.9, 1.2, 2.9, 2.3, 2.7, 2.5, 2.6, 3.5, 4.3, 460, 5

48, 0.5, 1.2, 1.3, 1.9, 2.1, 2.5, 2.7, 2.3, 3.4, 4.1, 430, 8

56, 0.6, 0.8, 1.3, 1.8, 3.6, 3.2, 2.4, 2.9, 3.5, 4.4, 560, 5

38, 0.4, 1.0, 2.1, 1.6, 2.4, 2.6, 2.8, 2.3, 3.6, 4.0, 400, 8

40, 0.5, 0.9, 1.2, 1.7, 2.5, 2.4, 2.7, 2.2, 3.4, 4.1, 490, 7

39, 0.6, 0.7, 2.0, 1.8, 2.2, 2.5, 2.6, 2.3, 4.8, 4.2, 580, 6

38, 0.4, 0.8, 1.9, 1.9, 2.3, 3.5, 2.7, 2.2, 3.9, 4.5, 455, 5

40, 0.5, 0.9, 1.2, 2.9, 2.4, 2.8, 2.9, 2.5, 3.7, 4.1, 450, 9

50,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.4,	460,	7
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	520,	6
48,	0.4,	1.1,	1.9,	1.9,	2.3,	3.5,	3.7,	2.2,	3.9,	4.5,	430,	5
39,	0.7,	1.2,	2.0,	2.2,	3.1,	3.2,	2.5,	2.4,	4.5,	4.3,	520,	7
39,	0.5,	0.9,	1.2,	1.7,	2.5,	2.4,	2.7,	2.2,	3.4,	4.1,	540,	7
40,	0.6,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	460,	6
38,	0.4,	0.8,	1.9,	1.9,	2.3,	3.5,	2.7,	2.2,	3.9,	4.5,	550,	5
55,	0.7,	0.9,	2.1,	2.0,	2.6,	3.2,	3.3,	2.9,	4.6,	4.4,	410,	9
52,	0.6,	1.3,	2.0,	2.8,	2.5,	4.5,	4.4,	2.4,	4.1,	4.3,	470,	7
38,	0.4,	1.0,	2.1,	1.6,	2.4,	2.6,	2.8,	2.3,	3.6,	4.0,	400,	8
40,	0.5,	0.9,	1.2,	1.7,	2.5,	2.4,	2.7,	2.2,	3.4,	4.1,	490,	7
39,	0.6,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	4.8,	4.2,	580,	6
38,	0.4,	0.8,	1.9,	1.9,	2.3,	3.5,	2.7,	2.2,	3.9,	4.5,	455,	5
40,	0.5,	0.9,	1.2,	2.9,	2.4,	2.8,	2.9,	2.5,	3.7,	4.1,	450,	9
50,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.4,	460,	7
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	520,	6
38,	0.4,	1.0,	2.1,	1.6,	2.4,	2.6,	2.8,	2.3,	3.6,	4.0,	400,	8
40,	0.5,	0.9,	1.2,	1.7,	2.5,	2.4,	2.7,	2.2,	3.4,	4.1,	490,	7
39,	0.6,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	4.8,	4.2,	580,	6
38,	0.4,	0.8,	1.9,	1.9,	2.3,	3.5,	2.7,	2.2,	3.9,	4.5,	455,	5
40,	0.5,	0.9,	1.2,	2.9,	2.4,	2.8,	2.9,	2.5,	3.7,	4.1,	450,	9
50,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.4,	430,	7
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	520,	6
48,	0.4,	1.1,	1.9,	1.9,	2.3,	3.5,	3.7,	2.2,	3.9,	4.5,	430,	5
39,	0.7,	1.2,	2.0,	2.2,	3.1,	3.2,	2.5,	2.4,	4.5,	4.2,	520,	7

42,	0.6,	0.8,	1.2,	2.9,	2.3,	2.7,	2.6,	2.6,	3.5,	4.3,	560,	5
48,	0.5,	1.2,	1.3,	1.9,	2.1,	2.5,	2.7,	2.3,	3.4,	4.1,	430,	8
55,	0.6,	0.9,	2.1,	2.2,	2.8,	3.1,	3.3,	2.9,	4.2,	4.4,	459,	6
42,	0.5,	1.2,	1.5,	2.5,	2.2,	4.4,	3.8,	2.4,	4.5,	4.1,	540,	7
38,	0.4,	0.9,	1.2,	1.7,	3.4,	2.4,	2.8,	2.2,	3.4,	4.4,	590,	5
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	500,	6
42,	0.5,	0.8,	1.2,	2.8,	2.3,	2.7,	4.2,	2.6,	3.5,	4.3,	460,	7
45,	0.4,	1.2,	1.3,	1.9,	2.1,	2.5,	2.7,	2.3,	3.4,	4.1,	430,	9
40,	0.6,	0.9,	1.2,	2.9,	2.4,	2.8,	2.9,	2.5,	3.7,	4.1,	450,	9
50,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.4,	460,	7
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	520,	6
48,	0.4,	1.1,	1.9,	1.9,	2.3,	3.5,	3.7,	2.2,	3.9,	4.5,	430,	5
39,	0.7,	1.2,	2.0,	2.2,	3.1,	3.2,	2.5,	2.4,	4.5,	4.3,	520,	7
38,	0.4,	1.0,	2.1,	1.6,	2.4,	2.6,	2.8,	2.3,	3.6,	4.0,	400,	8
40,	0.5,	0.9,	1.2,	1.7,	2.5,	2.4,	2.7,	2.2,	3.4,	4.1,	490,	7
39,	0.6,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	4.8,	4.2,	580,	6
38,	0.4,	0.8,	1.9,	1.9,	2.3,	3.5,	2.7,	2.2,	3.9,	4.5,	455,	5
40,	0.5,	0.9,	1.2,	2.9,	2.4,	2.8,	2.9,	2.5,	3.7,	4.1,	450,	9
50,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.4,	460,	7
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	520,	6
38,	0.4,	1.0,	2.1,	1.6,	2.4,	2.6,	2.8,	2.3,	3.6,	4.0,	400,	8
40,	0.5,	0.9,	1.2,	1.7,	2.5,	2.4,	2.7,	2.2,	3.4,	4.1,	490,	7
42,	0.7,	1.3,	1.9,	2.3,	3.2,	2.6,	3.8,	2.6,	3.7,	4.2,	500,	8
39,	0.6,	0.9,	1.6,	1.7,	2.1,	2.5,	2.6,	2.3,	3.6,	4.3,	400,	6
45,	0.4,	1.0,	1.5,	2.4,	2.4,	3.0,	2.5,	2.7,	3.4,	4.2,	450,	9

55, 0.7, 0.8, 1.3, 1.8, 3.6, 3.3, 2.4, 2.9, 4.5, 4.4, 560, 5

44, 0.4, 0.9, 2.0, 2.8, 3.4, 4.2, 3.5, 2.3, 3.6, 4.2, 500, 7

39, 0.7, 0.7, 2.0, 1.8, 2.2, 2.5, 2.6, 2.3, 3.8, 4.3, 520, 6

48, 0.4, 1.1, 1.9, 1.9, 2.3, 3.5, 3.7, 2.2, 3.9, 4.5, 430, 5

40, 0.5, 1.1, 1.8, 2.5, 3.1, 2.9, 2.6, 2.9, 3.6, 4.1, 460, 9

39, 0.7, 0.7, 2.0, 1.8, 2.2, 2.5, 2.5, 2.3, 3.8, 4.2, 520, 6

42, 0.5, 1.2, 1.5, 2.5, 2.4, 4.4, 3.8, 2.4, 4.2, 4.1, 540, 7

38, 0.4, 0.9, 1.2, 1.7, 3.4, 2.4, 2.8, 2.2, 3.4, 4.4, 590, 5

39, 0.7, 0.7, 2.0, 1.8, 2.2, 2.5, 2.6, 2.3, 3.8, 4.2, 500, 6

42, 0.5, 0.8, 1.2, 2.8, 2.3, 2.7, 4.2, 2.6, 3.5, 4.3, 460, 7

45, 0.4, 1.2, 1.3, 1.9, 2.1, 2.5, 2.7, 2.3, 3.4, 4.1, 430, 8

40, 0.5, 1.1, 1.8, 2.5, 3.1, 2.9, 2.6, 2.9, 3.6, 4.4, 460, 9

43, 0.6, 0.9, 1.5, 2.2, 2.8, 4.4, 3.8, 2.4, 4.2, 4.3, 540, 7

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57, 0.6, 0.9, 2.1, 2.2, 2.8, 3.1, 3.3, 2.9, 4.2, 4.4, 459, 6

51, 0.7, 0.8, 2.2, 1.7, 3.5, 3.2, 2.8, 2.3, 3.5, 4.3, 400, 5

40, 0.5, 1.1, 1.8, 2.5, 3.1, 2.9, 2.6, 2.9, 3.6, 4.1, 460, 9

46, 0.4, 0.9, 1.2, 1.7, 2.5, 2.4, 2.7, 2.2, 3.4, 4.4, 490, 7

39, 0.6, 0.7, 2.0, 2.5, 2.2, 2.5, 2.6, 2.3, 4.8, 4.2, 570, 6

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40,	0.5,	0.9,	1.2,	2.9,	2.4,	2.8,	2.9,	2.5,	3.7,	4.1,	450,	9
50,	0.7,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.4,	460,	7
39,	0.5,	1.2,	2.0,	2.2,	3.1,	3.2,	2.5,	2.4,	4.5,	4.3,	520,	7
42,	0.6,	0.8,	1.2,	2.9,	2.3,	2.7,	2.5,	2.6,	3.5,	4.2,	560,	5
48,	0.5,	1.2,	1.3,	1.9,	2.1,	2.5,	2.7,	2.3,	3.4,	4.1,	430,	8
55,	0.6,	0.9,	2.1,	2.2,	2.8,	3.1,	3.3,	2.9,	4.2,	4.4,	459,	6
42,	0.5,	1.2,	1.5,	2.5,	2.2,	4.4,	3.8,	2.4,	4.2,	4.1,	540,	7
38,	0.4,	0.9,	1.2,	1.7,	3.4,	2.4,	2.8,	2.2,	3.4,	4.3,	590,	5
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	500,	6
42,	0.5,	0.8,	1.2,	2.8,	2.3,	2.7,	4.2,	2.6,	3.5,	4.3,	460,	7
45,	0.4,	1.2,	1.3,	1.9,	2.1,	2.5,	2.7,	2.3,	3.4,	4.1,	430,	9
40,	0.6,	0.9,	1.2,	2.9,	2.4,	2.8,	2.9,	2.5,	3.7,	4.3,	450,	9
40,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.1,	460,	9
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	520,	6
42,	0.5,	1.2,	1.5,	2.5,	2.2,	4.4,	3.8,	2.4,	4.2,	4.1,	540,	7
38,	0.4,	0.9,	1.2,	1.7,	3.4,	2.4,	2.8,	2.2,	3.4,	4.4,	590,	5
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	500,	6
42,	0.5,	0.8,	1.2,	2.8,	2.3,	2.7,	4.2,	2.6,	3.5,	4.3,	460,	7
55,	0.6,	0.9,	2.1,	2.2,	2.8,	3.1,	3.3,	2.9,	4.2,	4.4,	459,	6
42,	0.5,	1.2,	1.5,	2.5,	2.2,	4.4,	3.8,	2.4,	4.7,	4.1,	540,	7
51,	0.7,	0.8,	2.2,	1.7,	3.5,	3.2,	2.8,	2.3,	3.5,	4.3,	400,	5
40,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.1,	460,	9
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	520,	6
42,	0.5,	1.2,	1.5,	2.5,	2.9,	4.4,	3.8,	2.4,	4.2,	4.1,	540,	7

38,	0.4,	0.9,	1.2,	1.7,	3.4,	2.4,	2.8,	2.2,	3.4,	4.4,	590,	5
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	500,	6
42,	0.5,	0.8,	1.2,	2.8,	2.3,	2.7,	4.2,	2.6,	3.5,	4.3,	460,	7
45,	0.4,	1.2,	1.3,	1.9,	2.1,	2.5,	2.7,	2.3,	3.4,	4.1,	430,	9
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38,	0.4,	1.0,	2.1,	1.6,	2.4,	2.6,	2.8,	2.3,	3.6,	4.0,	400,	8
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42,	0.7,	1.3,	1.9,	2.3,	3.2,	2.6,	3.8,	2.6,	3.7,	4.2,	500,	8
39,	0.6,	0.9,	1.6,	1.7,	2.1,	2.5,	2.6,	2.3,	3.6,	4.3,	400,	6
42,	0.5,	1.2,	1.5,	2.5,	2.2,	4.4,	3.8,	2.4,	4.2,	4.1,	540,	7
38,	0.4,	0.9,	1.2,	1.7,	3.4,	2.4,	2.8,	2.2,	3.4,	4.4,	590,	5
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	500,	6
42,	0.5,	0.8,	1.2,	2.8,	2.3,	2.7,	4.2,	2.6,	3.5,	4.3,	460,	7
45,	0.4,	1.2,	1.3,	1.9,	2.1,	2.5,	2.7,	2.3,	3.4,	4.1,	430,	9
40,	0.6,	0.9,	1.2,	2.9,	2.4,	2.8,	2.9,	2.5,	3.7,	4.3,	450,	9
42,	0.5,	1.2,	1.5,	2.5,	2.2,	4.4,	3.8,	2.4,	4.2,	4.1,	540,	7
51,	0.7,	0.8,	2.2,	1.7,	3.5,	3.2,	2.8,	2.3,	3.5,	4.3,	400,	5
40,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.1,	460,	9
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	520,	6
42,	0.5,	1.2,	1.5,	2.5,	2.2,	4.4,	3.8,	2.4,	4.2,	4.1,	540,	7
38,	0.4,	0.9,	1.2,	1.7,	3.4,	2.4,	2.8,	2.2,	3.4,	4.4,	590,	5
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	500,	6
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38, 0.4, 0.9, 1.2, 1.7, 3.4, 2.4, 2.8, 2.2, 3.4, 4.4, 590, 5

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51, 0.7, 0.8, 2.2, 1.7, 3.5, 3.2, 2.8, 2.3, 3.5, 4.3, 400, 5

40,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.1,	460,	9
46,	0.4,	0.9,	1.2,	1.7,	2.5,	2.4,	2.7,	2.2,	3.4,	4.4,	490,	7
39,	0.6,	0.7,	2.0,	2.5,	2.2,	2.5,	2.6,	2.3,	4.8,	4.2,	580,	6
38,	0.4,	0.8,	1.9,	1.9,	2.3,	3.5,	2.7,	2.2,	3.9,	4.5,	455,	5
40,	0.5,	0.9,	1.2,	2.9,	2.4,	2.8,	2.9,	2.5,	3.7,	4.1,	450,	9
50,	0.7,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.4,	460,	7
39,	0.5,	1.2,	2.0,	2.2,	3.2,	3.2,	2.5,	2.4,	4.5,	4.3,	520,	7
42,	0.6,	0.8,	1.2,	2.9,	2.3,	2.7,	2.5,	2.6,	3.5,	4.2,	560,	5
48,	0.5,	1.2,	1.3,	1.9,	2.1,	2.5,	2.7,	2.3,	3.4,	4.1,	430,	8
39,	0.6,	0.7,	2.0,	2.5,	2.2,	2.5,	2.6,	2.3,	4.8,	4.2,	580,	6
38,	0.4,	0.8,	1.9,	1.9,	2.3,	3.5,	2.7,	2.2,	3.9,	4.5,	455,	5
40,	0.5,	0.9,	1.2,	2.9,	2.4,	2.8,	2.9,	2.5,	3.7,	4.1,	450,	9
50,	0.7,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.4,	460,	7
40,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.1,	460,	9
51,	0.6,	0.8,	1.4,	2.9,	2.2,	4.2,	3.8,	2.4,	3.5,	4.3,	400,	5
42,	o.5,	1.2,	1.5,	2.5,	2.2,	4.4,	3.8	2.4,	4.7,	4.1,	540,	7
55,	0.6,	0.9,	2.1,	2.2,	2.8,	3.1,	3.3,	2.9,	4.2,	4.4,	459,	6
42,	0.5,	0.8,	1.2,	2.8,	2.3,	2.7,	4.2,	2.6,	3.5,	4.3,	460,	7
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	500,	6
38,	0.4,	0.9,	1.2,	1.7,	3.4,	2.4,	2.8,	2.2,	3.4,	4.4,	590,	5
42,	0.5,	1.2,	1.5,	2.5,	2.2,	4.4,	3.8,	2.4,	4.2,	4.1,	540,	7
39,	0.7,	0.7,	2.0,	1.8,	2.2,	2.5,	2.6,	2.3,	3.8,	4.2,	520,	6
40,	0.5,	1.1,	1.8,	2.5,	3.1,	2.9,	2.6,	2.9,	3.6,	4.1,	460,	9
40,	0.6,	0.9,	1.2,	2.9,	2.4,	2.8,	2.9,	2.5,	3.7,	4.3,	450,	9
45,	0.4,	1.2,	1.3,	1.9,	2.1,	2.5,	2.7,	2.3,	3.4,	4.1,	430,	9

APPENDIX - B

Underground mine support equipments:

Figure B.1. Hydraulic prop

Figure B.2. Friction Prop

Figure B.3. Yielding Steel Prop

Figure B.4. Pit Prop

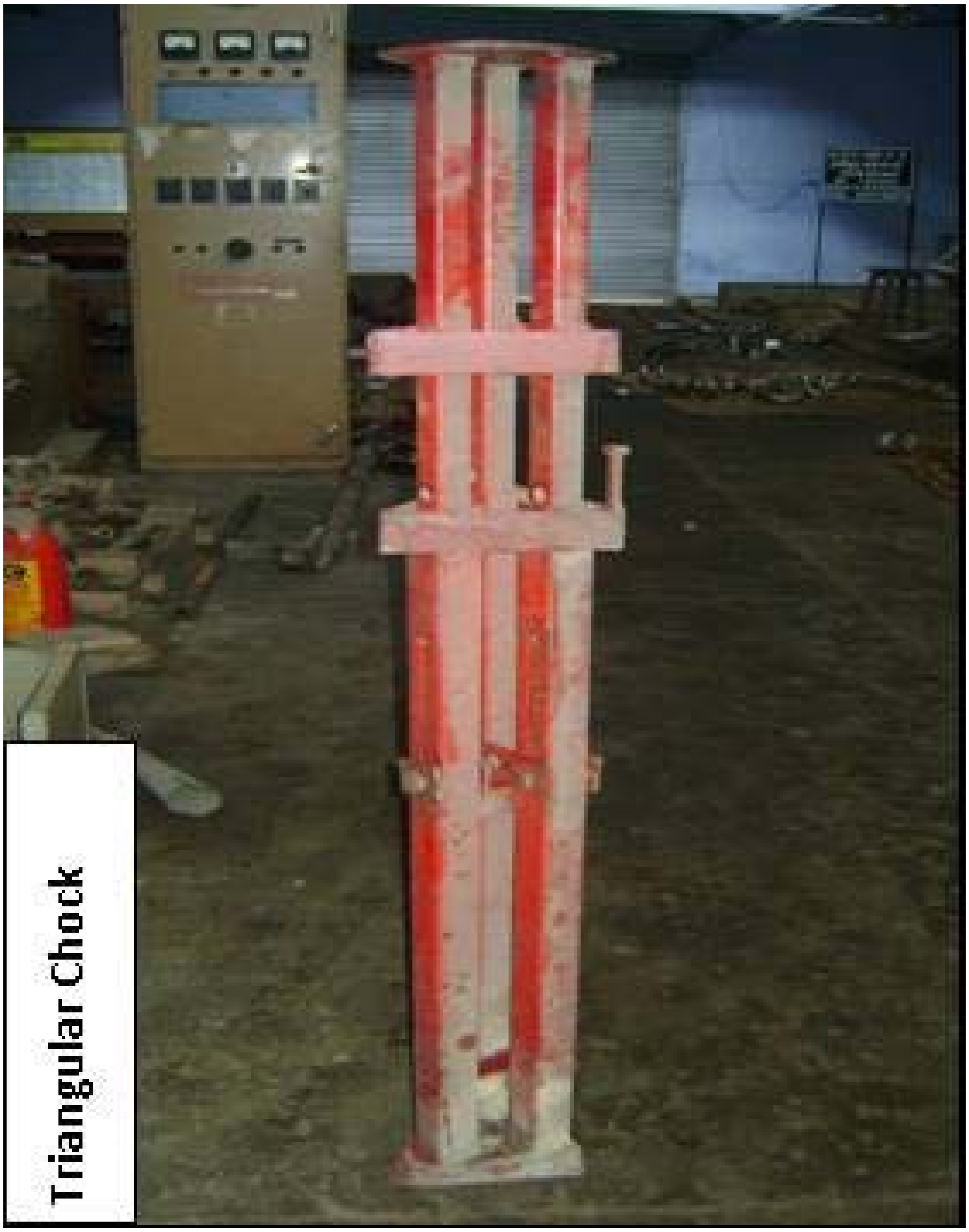

Figure B.5. Triangular Chock

Figure B.6. Friction Prop, Screw Prop and other props

Figure B.7. Twin hydraulic jack

Reference of photograph:

The above shown photographs were taken from the laboratory of Central Institute of Mining and Fuel Research, Dhanbad – 826015, Jharkhand, India.

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Published and Accepted Papers

Paper published /accepted in **international journals**

1. Parhi D.R; **S.K.Kashyap**; Sinha A" Prediction of Setting Load in Standing Support in Underground Mine Using ANN." - published in International Journal of Applied Artificial Intelligence in Engineering System. 2(1), 2010;27-37
2. Parhi D.R **; S.K.Kashyap** & Sinha A**.**'Analysis of rule based neuro-fuzzy technique used for prediction of setting load in standing support in underground mines,' published in International Journal of Applied Artificial Intelligence in Engineering System, 2(2)2010;119-122

3. Parhi D.R**; S.K.Kashyap** & Sinha A**.**'Neuro-fuzzy controller for prediction of setting load for standing support in underground mine. ' published in International Journal of Artificial Intelligence and Computational Research, 3(1), 2011; 39-41

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5. Parhi D.R**, S.K.Kashyap** & Sinha .A' Prediction of setting load in standing Support in underground mine using Neuro-Fuzzy controller'in International Journal of Artificial Intelligence and Computational Research. (Communicated)

6. Parhi D.R**, S.K.Kashyap** & Sinha .A" Analysis of soft computing technique for mine support" in International Journal of Applied Artificial Intelligence in Engineering System. (Communicated)

Paper published and to be presented in **international and national conferences**

1. **S.K Kashyap**; Parhi D.R; Sinha A; Singh M.K & Singh B.K "Optimisation of mine support parameters using Neural Network approach" presented at 12th IACMAG organized by IIT Mumbai on 1-6, October 2008 at Goa.

2. **S.K.Kashyap**; Parhi D.R; Sinha A" Artificial Neural Network – A Tool for Optimizing Mining Parameters "published in the proceeding of SINOROCK2009 at University of Hong Kong ,China on May,19-22 ,2009.

3. **S.K.Kashyap;**D.R.Parhi & A.Sinha "Application of fuzzy logic in Underground Mines in prediction of setting load of standing support" Accepted at 5th International Symposium on in-situ Rock Stress to be held on 25-27th August 2010, Beijing, China.

4. **S.K.Kashyap**, D.R.Parhi & A.Sinha 'Approximation of preload on prop in underground mine using fuzzy logic technique.' presented in 13th IACMAG 2011 in Australia.

5. **S.K.Kashyap**, D.R.Parhi & A.Sinha.' Application of fuzzy logic in UG mine in approx. of setting load on standing prop. Accepted in ICCMS2011 at Mumbai.

6. S.K.Kashyap,D.R.Parhi & A.Sinha, An Intelligent technique for mine support System. Presented in AMPS,2011,26-27 August,2011 at CIMFR, Dhanbad

7. **S.K.Kashyap**,D.R.Parhi & A.Sinha ' Intelligent Controller for Tunnel Support System : Fuzzy Logic Approach' accepted for presentation in WTC-2012, Bangkok.

8. **S.K.Kashyap**,D.R.Parhi & A.Sinha 'Application of neuro-fuzzy technique in mine support system for ground control'Accepted for presentation for ICGCM-2012, West Virginia , USA to be held on 31st July- 02Augist ,2012.

Brief Resume

Mr. Sudhir Kumar Kashyap is a Principal Scientist in the Department of Support Development & Testing, Central Institute of Mining and Fuel Research, Dhanbad – 826015, Jharkhand, India. He has more than 21 years of research experience in the field of underground mine support development and their testing. About 50 papers in national / international journals and conferences and 17 patents including one international patent are in his credit. He has handled more 50 research projects related with mining and allied machinery. This dissertation is being submitted for fulfillment of the PhD degree. The contact address is:

Sudhir Kumar Kashyap

Principal Scientist

Central Institute of Mining and Fuel Research

Barwa Road, Dhanbad – 826015, Jharkhand, India

Phone: 0326-2296074 (R), Fax: 0326-2296025(o)

Mob: 09431120003, E-mail: sudhirnutan@yahoo.com

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ANALYSIS OF RULEBASED-NEURO-FUZZY TECHNIQUE USED FOR PREDICTION OF SETTING LOAD IN STANDING SUPPORT IN UNDERGROUND MINE

D. R. Parhi*, Sudhir Kumar Kashyap and Amalendu Sinha****

Abstract: In this paper, a comprehensive analysis of rulebased-neuro-fuzzy technique has been done for prediction of setting load in underground mines. Some of the variable parameters associated with the underground excavation work have been taken as input/output parameter for the network. The technique of simulation of the result has also been discussed.

In practical situation it is very difficult to study the soil and rock behavior and to predict how the ground will behave during support. Analysis of underground mine accidents reveals that roof falls continue to remain the single largest killer. Empirical approaches has been widely used to design the mines support since long. In the present scenario intelligent decision plays an important role to avoid catastrophe. Such catastrophe can be avoided using the accurate measurement, optimization and analysis of data and using the rulebased-neuro-fuzzy technique.

Keywords: rule base, neural, fuzzy, mines support

1. INTRODUCTION

Now a days scientist and engineers are focusing on artificial intelligence technique to solve various engineering applications[1-8]. Some of the engineers have used [9-12] fuzzy logic technique to solve various mining related problem. Research are also going on artificial neural network [13-17] to solve various mining problem.

In the current analysis for prediction of setting load three types of artificial intelligence has been hybridized, namely fuzzy logic, neural network and rule based technique. This technique has been adopted to do a smooth and hazard free exploitation of coal in India ,which is a big problem since years. Using the methodology the support load can be automatically calculated without the empirical formula.

2. ANALYSIS OF INPUT AND OUTPUT DATA TO RULEBASED-NEURO-FUZZY CONTROLLER

Input: There are seven inputs to the Rulebased-Neuro-Fuzzy controller. They are described as follows;

(i) Rock Mass Rating (RMR): Rock mass classification systems such as Geomechanics classification (RMR) can be used as an effective parameter for calculation of support load immediately after tunnel excavation. It bases on five sub parameters. These parameters are:

(a) Uniaxial compressive strength of the rock

(b) Rock quality designation (RQD)

(c) Spacing of discontinuities

(d) Condition of discontinuity

(e) Ground water conditions.

* Professor, Mechanical Engineering, National Institute of Technology, Rourkela, Orissa-769008, India

** Scientist, Central Institute of Mining and Fuel Research, Barwa Road, Dhanbad-826015, India

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PREDICTION OF SETTING LOAD IN STANDING SUPPORT IN UNDERGROUND MINE USING ARTIFICIAL NEURAL NETWORK

D. R. Parhi*, Sudhir kumar Kashyap** and Amalendu Sinha**

Abstract: In many circumstances, our fundamental understanding of soil and rock behavior still falls short of being able to predict how the ground will behave. Cause-wise analysis of underground mine accidents reveals that roof falls continue to remain the single largest killer. Ground control operation is an 'imprecise' area of engineering due to the fact that we are dealing with a material produced by nature (the ground). Empirical approaches to design has been widely used in these mines since long. Under these circumstances, expert judgement plays an important role and Thus, such accidents can be obviated using the accurate measurement, optimization and analysis of data, a predictions based on previous results using one of the Artificial Intelligence technique i.e. Neural Networking. It is a simple computational model, which is analogous to that of neural system in human brain.

In this paper we have given a brief study on Neural Network Technology including Back Propagation Neural Network (BPNN) to train the network for optimization the mine support parameters. Some of the variable parameters associated with the underground excavation work have been taken as input/output parameter for the network. The technique of simulation of the result has also been discussed.

Keywords: mine support parameters, Neural Network. Backpropagation

1. INTRODUCTION

Recently researchers have put efforts to solve various application using neural network [1-8]. Some of the engineers [9-13] have also used neural network to solve mining problems.

Safely exploitation of coal in India has been a big problem since years. In terms of the method of winning coal. the share of opencast mining, which was as low as 14% in 1951, increased to current high level of above 80% whereas the share of underground mining declined from 77% in 1971 to current 20%. Even if, we can't ignore the underground mine coal production due to its good quality of coal as well as for societal reasons. In underground operation ground control problem is an important factor affecting safety, production and efficiency .A view of underground mines with sufficient support and drilling operation have been shown in fig. 1.

In terms of number of mines, out of about 595 operating mines, about 384 are underground mines. In underground coal mining technology, bord and pillar mining method is one of the major technology being used in India, with about 91% of the underground coal production. employing about 57% of total work force. As per statistics of accident data "fall of roof / sides" is one of the major cause of mine accidents. A major consideration in supporting mine roofs is limiting the movement and expansion of the rock strata immediately above the roof. Cause-wise analysis of mine accidents reveals that roof falls continue to remain the single largest killer, As many as 61% of the incidences. which is 28.5% of total fatalities are due to roof fall. Such accidents can be obviated using the accurate measurement and optimization of data and its analysis using Artificial Intelligence. Since artificial intelligence (AI) techniques can make use of heuristic knowledge (rules of thumb) or pattern matching techniques, as opposed to solving a set of mathematical equations. they should be ideally suited for application in the field of geotechnical

* Professor. Mechanical Engineering, National Institute of Technology, Rourkela, Orissa-769008, India

** Scientist. Central Institute of Mining and Fuel Research, Barwa Road. Dhanbad-826015, India

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International Association for Computer Methods and Advances in Geomechanics (IACMAG)
1-6 October, 2008
Goa, India

Optimization of Mine Support Parameters Using Neural Network Approach

S.K.Kashyap*, D.R.K.Parhi**
**Scientist, CIMFR, Barwa Road, Dhanbad – 826001*
*** Asst. Professor, N.I.T. Rourkela – 769008*

A.Sinha*, M.K.Singh, B.K.Singh****
** Scientist, CIMFR, Barwa Road, Dhanbad – 826001*
***Research Scholar, N.I.T Rourkela - 769008*

Keywords: mine support parameters, optimisation, Neural Network

ABSTRACT: Since ground control operation is an 'imprecise' area of engineering due to the fact that we are dealing with a material produced by nature (the ground). In many circumstances, our fundamental understanding of soil and rock behavior still falls short of being able to predict how the ground will behave. Cause-wise analysis of mine accidents reveals that roof falls continue to remain the single largest killer. Under these circumstances, expert judgement plays an important role, and empirical approaches to design are widely used. Such accidents can be obviated using the accurate measurement, optimization and analysis of data a predictions based on previous results using one of the Artificial Intelligence technique i.e. Neural Networking. It is a simple computational model, which is analogous to that of neural system in human brain. In this paper we have focused Neural Network Technology including Back Propagation Neural Network (BPNN) to train the network for optimization the mine support parameters. Some of the variable parameters associated with the underground excavation work have been taken as input parameter for the network. By simulation the result was compared with the target output until the network error has converged to a threshold minimum.

1. Introduction

India has a large proven reserve of coal as compared to other fuel energy sources. Safely exploitation of coal has been a big problem since years. In terms of the method of winning coal, the share of opencast mining, which was as low as 14% in 1951, increased to current high level of above 80% whereas the share of underground mining declined from 77% in 1971 to current 20%.Even if, we can't ignore the underground mine coal production due to its good quality of coal as well as for societal reasons. In underground operation ground control problem is an important factor affecting safety, production and efficiency .A view of underground mines with sufficient support and drilling operation have been shown in fig.1. As per statistics of accident data "fall of roof / sides" is one of the major cause of mine accidents. A major consideration in supporting mine roofs is limiting the movement and expansion of the rock strata immediately above the roof. Cause-wise analysis of mine accidents reveals that roof falls continue to remain the single largest killer, As many as 61% of the incidences, which is 28.5% of total fatalities are due to roof fall. In underground coal mining technology, bord and pillar mining method is one of the major technology being used in India, with about 91% of the underground coal production, employing about 57% of total work force. In terms of number of mines, out of about 595 operating mines, about 384 are underground mines. Such accidents can be obviated using the accurate measurement and optimization of data and its analysis using Artificial Intelligence. Since artificial intelligence (AI) techniques can make use of heuristic knowledge (rules of thumb) or pattern matching techniques, as opposed to solving a set of mathematical equations, they should be ideally suited for application in the field of geotechnical engineering. Many aspects of mine design are based upon empirical data. The availability of data and knowledge is two important considerations in implementing many engineering and scientific applications. It is especially true to application problems in mining industry. However , there are many difficulties associated with the utilization of both data and knowledge. The first difficulty is for instance, model identification, when huge volumes of observable geoscientific data are available. With the conventional techniques such as statistical regression is still hard to find a satisfactory solutions because there are too many variables and assumptions involved.

ARTIFICIAL NEURAL NETWORK – A TOOL FOR OPTIMISING MINING PARAMETERS

Sudhir kumar Kashyap
Scientist, CIMFR, Barwa Road, Dhanbad – 826015(INDIA)

D.R.Parhi
Professor, N.I.T. Rourkela – 769008 (INDIA)

Amlendu Sinha
Scientist, CIMFR, Barwa Road, Dhanbad – 826015(INDIA)

ABSTRACT:

In many circumstances, our fundamental understanding of soil and rock behavior still falls short of being able to predict how the ground will behave. Cause-wise analysis of mine accidents reveals that roof falls continue to remain the single largest killer. Ground control operation is an 'imprecise' area of engineering due to the fact that we are dealing with a material produced by nature (the ground). Under these circumstances, expert judgement plays an important role, and empirical approaches to design are widely used. Thus,such accidents can be obviated using the accurate measurement, optimization and analysis of data a predictions based on previous results using one of the Artificial Intelligence technique i.e. Neural Networking. It is a simple computational model, which is analogous to that of neural system in human brain.

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Keywords: mine support parameters, optimisation, Neural Network

1.INTRODUCTION

Safely exploitation of coal has been a big problem since years. In terms of the method of winning coal, the share of opencast mining, which was as low as 14% in 1951, increased to current high level of above 80% whereas the share of underground mining declined from 77% in 1971 to current 20%. Even if, we can't ignore the underground mine coal production due to its good quality of coal as well as for societal reasons. In underground operation ground control problem is an important factor affecting safety, production and efficiency .A view of underground mines with sufficient support and drilling operation have been shown in fig.1.

Figure 1.Underground Mine with Support and Drilling Operation

In terms number of mines, out of about 595 operating mines, about 384 are underground mines. In underground coal mining technology, bord and pillar mining method is one of the major technology being used in India, with about 91% of the underground coal production, employing about 57% of total work force. As per statistics of accident data "fall of roof / sides" is one of the major cause of mine accidents. A major consideration in supporting mine roofs is limiting the movement and expansion of the rock strata immediately above the roof. Cause-wise analysis of mine accidents reveals that roof falls continue to remain the single largest killer. As many as 61% of the incidences, which is 28.5% of total fatalities are due to roof fall. Such accidents can be obviated using the accurate measurement and optimization of data and its analysis using Artificial Intelligence. Since artificial intelligence (AI) techniques can make use of heuristic knowledge (rules of thumb) or pattern matching techniques, as opposed to solving a set of mathematical equations, they should be ideally suited for application in the field of geotechnical engineering. Many aspects of mine design are based upon empirical data. The availability of data and knowledge are two important considerations in implementing many engineering and scientific applications.

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Dr.-Ing. habil. Markus Oeser
School of Civil and Environmental Engineering
UNSW, Sydney, NSW, 2052
Telephone: +61 (2) 9385 5016
Fax: +61 (2) 9385 6139
Email: info@iacmag2011.com

March 11, 2011

Dear Dr S Kashyap,

On behalf of the IACMAG2011 Organising Committee, we are pleased to advise that your contribution:

Paper no: 1296
Entitled: Approximation of preload on prop in underground mine using fuzzy logic technique

Has been accepted for **oral presentation and publication** in the proceedings of IACMAG2011 Conference.

We are pleased to acknowledge receipt of your revised paper and all associated details and wish to invite you to attend IACAM Conference in Melbourne Australia from 9 to 12 May 2011.

For the latest updates on *IACMAG 2011*, please visit the website www.IACMAG2011.com. If you have any questions, please contact us at info@iacmag2011.com.

We encourage you to register and pay the registration fees as soon as possible. All details for registration can be found in www.iacmag2011.com/registration.html.

We look forward to seeing you both in Melbourne 09-11 May 2011.

Kind regards,

Markus Oeser
IACMAG Conference Secretariat